Establishing normative hand transport tangential velocity of a reach-to-grasp task : towards an objective assessment for UE stroke rehabilitation

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**ESTABLISHING NORMATIVE HAND TRANSPORT
TANGENTIAL VELOCITY OF A REACH-TO-GRASP TASK:
TOWARDS AN OBJECTIVE ASSESSMENT FOR UE STROKE
REHABILITATION**

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List of Symbols and Abbreviations

ADL	Activity of daily living
ANey	Adaptive Neyman test.
ANOVA	Analysis of variance.
AperE	Aperture event defined as mean of time of aperture closure initiation and time of max aperture closing velocity.
AperE_Time	Proportion of movement duration of occurrence of AperE.
AperE_TV _{el} _Amp	Amplitude of hand transport TV _{el} when AperE occurred.
ARAT	Action Research Arm Test
BI	Barthel Index
CIMT	Constraint induced movement therapy
CMSA	Chedoke-McMaster Stroke Assessment
CNS	Central nervous system
<i>CORT</i>	Temporal correlation that is global trend effect free.
<i>cross-ApEn</i>	Cross approximate entropy.
c_T	Cutoff frequency.
CUBE	Reach-supinate-to-grasp cube task
<i>CV</i>	Coefficient of variation.
CYL	Reach-supinate-to-grasp cylindrical object task
DFD	Discrete Frechet distance.
DST	Dynamic system theory
$\delta_F(f, g)$	Frechet distance between 2 continuous curves f and g .
$\delta_{dF}(P, Q)$	DFD between 2 time series P and Q with discrete time points.
<i>DisNor</i>	Shortest distance from a (<i>CORT</i> , <i>PIN</i>) position to the ‘normal area’.
$EM_k = \frac{\sum_{i=1}^N V_{i,k}}{N}$	Ensemble mean curve for k^{th} discrete time point. $V_{i,k}$ is the tangential velocity of i^{th} curve (trial) at the k^{th} time point.
EM_TV _{el}	Ensemble mean tangential velocity
FMA	Fugl-Meyer Assessment
$gap(k)$	Gap statistic. Optimal number of cluster, k , corresponds to the maximum $gap(k)$ value.
GMP	Generalised Motor Program
HSD	Tukey’s honestly significant difference.
ICIDH	International Classification of Impairments, Disabilities, and Handicaps
<i>Itr</i>	Iteration number.
Jerk	Normalised jerk metric. A measure of temporal smoothness.

JHFT	Jebsen-Taylor Hand Function Test
$KL(v, u)$	Kullback-Leibler divergence measure between two non-negative functions v and u .
κ	3D curvature.
k -means	k -means clustering algorithm.
LE	Lateral epicondyle marker.
LTN	Linear time normalisation.
MAS	Motor Assessment Scale
$MaxLag(u-v)$	Number of percentage time point curve v needs to be shifted in order to achieve maximum PPMC with curve u .
MBI	Modified Barthel Index
MCP	Metacarpal-phalangeal
ME	Medial epicondyle marker.
MedianLC	Median of distribution of $-\ln(\kappa)$. A measure of spatial smoothness.
MOH	Ministry of Health
NDT	Neurodevelopmental treatment
NRDO	National Registry of Diseases Office
NTN	Nonlinear time normalisation via procedure proposed in Chapter 4 using 3 temporal landmarks.
NTN4	Set of NTN TVel curves that are subjected to one additional adjustment using movement onset, maximum TVel, AperE and movement offset times.
NTN5	Set of NTN TVel curves that are subjected to one additional adjustment using movement onset, SupE, maximum TVel, AperE and movement offset times.
ORG	Original data with no time normalisation.
PIN	Proportion of movement duration that a TVel profile falls within a 95% prediction interval of normative EM_TVel profile.
PIP	Proximal interphalangeal
PPC	Posterior parietal cortex
$PPMC$	Pearson product moment correlation.
QTM	Qualisys Track Manager software
RMS	Root mean square
RS	Radius styloid process marker.
SDFD	Minimum sum ‘path’ that contains the DFD in the free space.
SD_{Itr}	A set of collection of all the SD_k for each iteration. Itr is iteration number.

SD_k	Standard deviation of TVel at the k^{th} time point.
SUP	Reach-supinate-to-touch cylindrical object task
SupE	Supination event defined as mean of time of max supination acceleration and time of max supination velocity.
SupE_Time	Proportion of movement duration of occurrence of SupE.
SupE_TVel_Amp	Amplitude of hand transport TVel when SupE occurred.
sw	Average silhouette width.
sw_i	Silhouette width for observation i .
T_{AN}^*	ANey test statistic.
T_{AN}	Standardised ANey test statistic.
TC	Time-to-contact
t_{ij}	Time of occurrence of the j^{th} ($j = 1, \dots, M$) landmark for the i^{th} ($i = 1, \dots, N$) curve
T_j	Mean time location of the j^{th} landmark and is also the target location for all the N number of j^{th} landmarks
TOU	Reach-to-touch task
TVel	Tangential velocity
UCM	Uncontrolled manifold.
UE	Upper extremity
US	Ulnar styloid process marker.
$V = \sqrt{V_x^2 + V_y^2 + V_z^2}$	Mathematical formula for calculating TVel. V_x , V_y and V_z are the velocities of the x , y and z position components.
V_{Direct}	Warped TVel when warping is done directly in the TVel domain.
VE	Virtual marker that is mid-point of ME and LE.
WHO	World Health Organisation
w_i	Warping function for the i^{th} curve
WMFT	Wolf Motor Function Test

Summary

An objective assessment system for stroke upper extremity (UE) rehabilitation is long overdue. With advancements in human motion capture technology and UE biomechanical modelling, kinematic analysis of UE functional tasks is fast becoming a viable option that supplements current clinical assessment practises. Importantly, kinematic analysis has been shown to be reliable, objective and sensitive. Furthermore, it does not suffer from floor and ceiling effects. Reach-to-grasp is one of the most common UE therapeutic and assessment functional activities used in both clinical and research settings. The hand transport tangential velocity (TVel) profile is widely used to characterise the performance of a reach-to-grasp task and is sensitive to deviation from normal movement. Hence, this study aims to contribute towards the development of an objective assessment system for stroke UE rehabilitation by using the hand transport TVel profile of 2 reach-to-grasp tasks.

In this study, a criterion-referenced approach is used. For the purpose of establishing a ‘normal’ criterion for the reach-to-grasp tasks, normative hand transport TVel profiles are obtained from a sample of healthy subjects using a repeated measure experimental design. In order to construct accurate normative hand transport TVel profiles, intra and inter subject TVel temporal variances need to be minimised so as to reduce erroneous TVel amplitude variances. A novel nonlinear time normalisation procedure is proposed to reduce intra-subject TVel temporal variance. This procedure is based on the landmark curve registration technique. Important kinematic landmarks are identified via detailed comparisons of hand transport TVel profiles between different experimental conditions. Inter-subject temporal variance is reduced by means of identifying clusters (groups) of identical hand transport TVel profiles using the k -means algorithm. As a result, it is determined that multiple groups of normal hand transport TVel profile exist for the 2 reach-to-grasp tasks in this study.

A pilot trial involving hemiplegic stroke patients is conducted. A novel objective assessment method based on the normative hand transport TVel profiles is proposed. This method quantifies a patient’s reach-to-grasp performance by comparing his hand transport TVel profile amplitude and temporal correlation with the normative hand transport TVel profiles. It is clearly demonstrated that the proposed method is capable of detecting pathological reach-to-grasp movements.

Chapter 1

Introduction

1.1 Background and rationale

Stroke is a medical condition when the supply of blood to the brain is impaired by blockage (ischemic) or rupture (haemorrhagic) of an artery to the brain leading to the death of brain cells. According to a health fact sheet on stroke trends between 2005 and 2010 published by Ministry of Health (MOH) and the National Registry of Diseases Office (NRDO) Singapore in 2012, stroke is the 4th leading cause of death and the incidence of new stroke in 2010 is 1.8/1000 for those aged between 15 and 64 years old. This is equivalent to approximately 6700 new cases of stroke for this age group in 2010. Venketasubramanian et al. (2005) found that the crude prevalence rate of new stroke is 4.05% among 14906 Singaporeans who are 50 years and older. Conceivably, the burden of stroke is expected to increase with an ageing population (Venketasubramanian & Chen, 2008).

One of the more common impairments after stroke is hemiparesis which is a consequence of interruption of motor signals that pass via the corticospinal tract to the spinal cord motor neurons (Ward, 2005). Less than 20% of stroke survivors recover full upper extremity (UE) functions (Kwakkel et al., 2003; Nakayama et al., 1994; Wade et al., 1983) while some levels of UE dexterity have been observed in less than 40% of chronic stroke patients (Kong, Chua & Lee, 2011; Kwakkel et al., 2003). With medical advancements, more stroke victims have survived. Although pharmacological advances in stroke therapy have resulted in ability to reduce infarct size and minimize loss of functionality (Ringleb, 2006), for a large proportion of stroke patients, the affected UE remains as a passive object to be cared for (Ashford et al., 2008). This results in difficulties to arise in performing activities of daily living (ADLs) independently, as well as limited participation in community activities (Pang, Harris & Eng, 2006). Thus, UE rehabilitation remains a pertinent challenge and continues to receive much deserved attention in clinical and research settings.

An important component of a successful stroke rehabilitation program is the ability to monitor and assess the effectiveness of rehabilitation interventions (Ashford et al., 2008). As stroke is a highly heterogeneous condition, an accurate assessment will in turn result in better

customization of therapy for individual patients. Furthermore, as clinical rehabilitation welcomes the introduction of advanced technologies, such as robotics, brain-computer interface, virtual reality etc, appropriate outcome measures are needed to assess the efficacy of these new treatment methods. Indeed, Duncan, Jorgense and Wade (2000) note in their systematic review on 51 major stroke trials that failure to detect beneficial changes in 21 of these trials may have been due to the selected outcome measures, thus resulting in non-acceptance of newly proposed interventions.

Assessment of functional and motor recovery from stroke, in both clinical and research settings, have conventionally been accomplished via various outcome measure scales, broadly categorized as (i) neurological deficit (impairment), (ii) functional outcome (disability), (iii) global outcome (handicap) and (iv) health-related quality-of-life (handicap) scales (Lyden & Hantson, 1998). It is believed that the knowledge of expected pattern of recovery will allow for a rational design of interventional trials (Duncan et al., 1992) eventually leading to implementation of more effective treatment methods. However, ordinal scales do not explain the underlying causes of motor dysfunction (Coderre et al, 2010; McCrea, Eng & Hodgson, 2002; Pomeroy & Tallis, 2002) and global outcome scales are deemed to be inadequate in capturing the process of motor recovery (Gladstone, Danells & Black, 2002) and may not have the resolution to detect specific and small changes that may be clinically significant (Ashford et al., 2008; Coderre et al., 2010; McCrea et al., 2002). Furthermore, the use of qualitative descriptors to score (categorise) movement quality of UE functional task such as reach-to-grasp suffers from subjective interpretation to certain degree. Unfortunately, measurement of movement quality is rarely conducted objectively (Pomeroy et al., 2003) and can be flawed with low inter-therapist agreement when therapists use different internal judgement models based on their personal definition of normative behaviour when visual analogue scale is used to assess quality of movement (Bernhardt, Bate & Matyas, 1998; Pomeroy et al., 2003).

Kinematic movement analysis has the potential to provide an objective mean of assessing movement quality. Various studies have demonstrated the repeatability, validity and discriminative power of kinematic analysis in the assessment of UE functions in stroke patients (Mackey et al., 2005; Murphy, Willen, & Sunnerhagen, 2010; Wagner et al., 2006; Subramania et al., 2010). In some studies (Caimmi et al., 2008; Wu et al., 2007), kinematic analyses are used as a relative measure to evaluate treatment effects against a pre-treatment

baseline. While useful in objectively and quantitatively determining effectiveness of treatment, such analyses do not measure the severity of movement deficit. On the other hand, others have attempted to construct normative (mean) kinematic curves of angular parameters to characterize specific UE tasks against which pathological movements can be compared and movement quality assessed quantitatively (Butler et al., 2010; Murgia, Kyberd & Barnhill, 2010; Petuskey et al., 2007; van Andel et al., 2008). Deviation from these normative mean curves can then be quantified to provide a measure of the severity of movement deficit.

Unlike gait analysis, there is no single most relevant UE functional task that can fully demonstrate the wide variety of UE functions (van Andel et al., 2008). Nevertheless, reach-to-grasp is an important function in many activities of daily living and is thus commonly used in stroke UE rehabilitation and assessment of treatment outcome. Commonly used functional scales such as Motor Assessment Scale (Carr et al., 1985), Action Research Arm Test (ARAT) (Lyle, 1981), Jebsen-Taylor Hand Function Test (Jebsen et al., 1969), Box and Block (Mathiowetz et al., 1985) and Wolf Motor Function Test (Wolf et al., 2005) are just a few among many clinical assessment tools that include elements of reach-to-grasp.

Hence, this study aims to construct normative representative mean curve(s) for the selected kinematic parameter(s) that characterize a normal reach-to-grasp task. In order to facilitate this, a group of normal healthy participants from a wide age group will be recruited to perform a reach-to-grasp task subjected to a repeated measure experimental design. As intra-subject variability and an even higher level of inter-subject variability are expected to exist, a process of time normalization needs to be performed prior to the calculation of an ensemble mean curve that represents the ‘average’ performance of an individual subject or group. Linear time normalization method which defines start of a task as 0% and the end of the task as 100% is often used. However, Rau, Disselhorst-Klug and Schmidt (2000) cautioned, among other issues pertaining to adopting gait analysis techniques for UE analysis, that while this method is applicable in gait analysis in which the movement is periodic and cyclic, it is generally not applicable to UE tasks. Thies et al. (2009) illustrated that linear time normalization for UE tasks introduced the risk of aligning trials inappropriately and proposed the use of dynamic time warping method to align the trials. Clearly, time normalization of UE kinematic data is a necessary step to minimize the adverse effect of temporal variation due to trials misalignment. It is a crucial step that directly affects the validity and accuracy of the resulting ensemble mean curve.

1.2 Objective

Ultimately, this study aims to contribute towards the development of a more objective upper extremity assessment for stroke rehabilitation by establishing normative kinematics of a reach-to-grasp task against which pathological movements can be compared. Maximising clinical viability and the chance of eventual implementation shall be a key criterion in this development.

In order to achieve this objective, the specific goal of this study is to reduce intra- and inter-subject temporal variances that contribute to an erroneous level of amplitude variance commonly observed in time series of reach-to-grasp kinematics. It is believed that this will consequently increase the accuracy in establishing normative kinematics which in turn is hypothesized to be more accurate in detecting deviations from normal movement.

1.3 Scope

The scope of this study includes:

- (i) Determine a set of kinematic parameter(s) that adequately characterizes a reach-to-grasp task. Such parameter(s) should have at least one invariant feature across different subjects that allows for construction of normative reach-to-grasp movement kinematic. In the case that a parameter is a time series, one possible invariant feature can be the shape of the time series curve. Also, the selected set of parameter(s) must exhibit detectable changes in the case of pathological reach-to-grasp movement.
- (ii) A reach-to-grasp experiment with healthy subjects:
 - a. Propose a nonlinear time normalization technique that performs better than the conventional linear time normalization technique in normalizing the time of individual trials for each subject. This will also include determination of key kinematic events in a reach-to-grasp task that are useful for time normalization. This is aimed at reducing intra-subject temporal variance that contributes to an erroneous level of amplitude variance.
 - b. Normative ensemble mean profiles(s) for the selected kinematic parameter(s) will be constructed based on experimental results. If necessary, subjects will be divided into different groups based on some common features. Normative ensemble mean profile(s) will then be constructed for each group. This is

aimed at reducing inter-subject temporal variance that contributes to an erroneous level of amplitude variance.

- (iii) A pilot patient trial:
 - a. Patients' performance will be used to verify the accuracy of the constructed normative ensemble mean profiles(s) for the selected kinematic parameter(s).
 - b. Illustrate the use of the normative ensemble mean profile(s) to provide an objective measure of deviation from normal movement for the patients.

1.4 Organization

Chapter 2 provides literature reviews that include (i) current clinical assessment methods, (ii) kinematic analysis of upper extremity motion in rehabilitation, (iii) motor control and neuroscience of reaching and reach-to-grasp, (iv) time normalization of kinematic curves and (v) kinematics of reach-to-grasp tasks. Justifications for the use hand transport tangential velocity to characterize a reach-to-grasp task is provided. Important temporal landmarks to be used for nonlinear time normalization of the hand transport tangential velocity profiles will also be identified.

Chapter 3 describes an experiment with healthy subjects performing reaching, reach-to-touch and reach-to-grasp tasks. These tasks are designed to determine the set of important forearm supination and grasping kinematic events that affect the hand transport tangential velocity.

Chapter 4 uses the temporal landmarks identified in Chapter 2 in the development of a novel nonlinear time normalization technique. This technique is applied to perform nonlinear time normalization of the hand transport tangential velocity profiles obtained in Chapter 3 to reduce temporal variance that contributes to an erroneous level of intra-subject amplitude variance. For each subject, hand transport ensemble mean tangential profiles are then constructed for each of the 4 tasks.

Chapter 5 compares and contrasts, for each subject, the hand transport ensemble mean tangential velocity profiles for the 4 tasks so as to identify forearm supination and grasping kinematic events that may possibly affect the hand transport tangential velocity profiles.

Chapter 6 assesses the identified key kinematic events from Chapter 5 for their viability as additional temporal landmarks to provide final time normalizing adjustment to the hand

transport tangential velocity. Reduction of temporal variance that contributes to an erroneous level of inter-subject amplitude variance is discussed. Normative hand transport ensemble mean tangential velocity profiles will be constructed on the group level.

Chapter 7 describes a pilot patient trial. Patients' hand transport tangential velocity profiles are assessed against the established normative hand transport ensemble mean tangential velocity profiles obtained in Chapter 6. An objective measure of deviation from normal movement is proposed.

Chapter 8 concludes with key contributions made in this study and future work is discussed.

Chapter 2

Literature Review

2.1 Review on some common stroke outcome measures

In accordance with the World Health Organisation (WHO) the International Classification of Impairments, Disabilities, and Handicaps (ICIDH) framework for classifying functioning and disability (WHO, 1999), stroke outcomes can be assessed at the body, individual (activity) and social (participation) levels (Figure 2.1). Relevant to the scope of this study, the focus shall be on the body and individual levels which are concerned with impairments and disabilities due to stroke. As such, some impairment and disability scales that are commonly used in clinical and/or research settings for assessing hemiplegic UE will be reviewed.

Figure 2.1: Framework for classifying functioning and disability. Source: WHO (1999).

There are two main therapeutic approaches (Table 2.1) in stroke rehabilitation, namely (i) neurophysiological and (ii) task-oriented approach (Mathiowetz & Bass-Haugen, 2008). The neurophysiological approach consists of traditional methods such as the Brunnstrom's movement therapy and Bobath's neurodevelopmental treatment (NDT). It is based on the reflex-hierarchical model of motor control and the neuromaturational theory of motor development. The reflex-hierarchical model implies all movements are elicited by sensory input or controlled by central programs and that the environment plays a minimal role. The neuromaturational theory of motor development assumes that the environment and experience do not play a role in determining structural changes in the central nervous system (CNS). In a

nutshell, the neurophysiological approach assumes that the CNS is hierarchically organized in that repetitive movement results in positive permanent changes in CNS in a predictable sequence with no interaction with the environment and experience of patient.

Table 2.1: Comparison of neurophysiological and task-oriented approach. Adapted from Mathiowetz and Bass-Haugen (2008).

Neurophysiological	Task-oriented
Models of Motor Control	
Reflex-Hierarchical <ul style="list-style-type: none"> • Movements are elicited by sensory input or controlled by central programs. • Open-loop and closed-loop control is used. • Feedback and feed-forward influence movements. • CNS is hierarchically organized, with higher centers controlling lower centers. • Reciprocal innervation is essential for coordinated movement. 	Systems <ul style="list-style-type: none"> • Personal and environmental systems interact to achieve functional goals. • Movement emerges from the interaction of many systems. • Systems are dynamical, self-organizing and heterarchical. • Movement used for a task is the preferred means for achieving a functional goal. • Changes in one or more systems can alter behaviour.
Theories of Motor Development	
Neuromaturational <ul style="list-style-type: none"> • Changes are due to CNS maturation. • Development follows a predictable sequence. • CNS damage leads to regression to lower levels and more stereotypical behaviours. 	Systems <ul style="list-style-type: none"> • Changes are due to interaction of multiple systems. • Progression varies because person and environmental contexts are unique. • CNS damage leads to attempts to use remaining resources to achieve functional goals.
Assumptions of Therapeutic Approaches	
<ul style="list-style-type: none"> • CNS is hierarchically organized. • Sensory stimuli inhibit spasticity and abnormal movement and facilitate normal movement and postural responses. • Repetition of movement results in positive permanent changes in CNS. • Recovery from CNS damage follows a predictable sequence. • Behavioural changes after CNS damage have a neurophysiological basis. 	<ul style="list-style-type: none"> • Personal and environmental systems, including the CNS, are heterarchically organized. • Functional tasks help to organize behaviour. • Occupational performance emerges from the interaction of persons and their environment. • Recovery is variable because personal characteristics and environmental contexts are unique. • Behavioural changes reflect attempts to compensate and to achieve task performance.

Contrary to the assumptions of the neurophysiological approach, the task-oriented approach assumes that motor behaviour emerges from the interaction between the person and the environment and is considered to be self-organising (Mathiowetz & Bass-Haugen, 2008).

Recent researches in neuroscience have demonstrated the brain's capability of reorganization

throughout a person's lifespan. Dobkin (1996) defines neuroplasticity to generally refer to use-dependent neuronal network modifications which include short-term modulations of function and long-term structural changes. From this perspective, Carr and Shepherd (2008) conclude that the process of novel skill acquisition in an intact CNS is in many ways similar to the process of regaining skills in a post-lesion CNS. Dobkin (2003) believes that experience and training induce physiological and morphological plasticity after stroke and recommends implementation of well-defined rehabilitation methods to achieve optimal manipulation of rehabilitation-induced neural adaptations that produce behavioural gains. In other words, this approach places heavy emphasis on the role that patients play during rehabilitation as well as the context in which this rehabilitation is being carried out. The desired outcome of this approach is to achieve a preferred set of movement patterns that is stable and yet flexible (Bass-Haugen, Mathiowetz & Flinn, 2008). Stability of movement pattern is characterized by a consistent performance in a constant environment while flexibility of movement pattern allows for adaptations to take place when the environment changes (Bass-Haugen, Mathiowetz & Flinn, 2008). Hence, the main difference between an outcome measure based on task-oriented approach and another based on neurophysiological approach is the use of real-life or simulated functional tasks in the former.

The Fugl-Meyer Assessment (FMA) scale is specifically developed to measure hemiplegic stroke recovery at the impairment level (Gladstone, Danells & Black, 2002; Lyden & Hantson, 1998). It is the second most frequently used assessment tool for patients with neurological deficit (van Wijck et al., 2001). The UE section of FMA consists of thirty three items each of which is scored with a 3-point ordinal scale from '0' to '2'. Qualitative descriptors of expected outcome are provided for each score. This is used by trained therapists to score the patients' performances. The test items evaluate reflex, synergy, coordination and range of motion of the shoulder, elbow, wrist and finger joints. The selection of these test items is believed to be based on the Brunnstrom six stages of stroke recovery (Brunnstrom, 1966; Gladstone et al., 2002; Mathiowetz & Bass-Haugen, 2008) and is thus well grounded in the neurophysiological approach to stroke rehabilitation. As such, the FMA provides a measure of severity of neurological deficit based on the assumptions of the neurophysiological approach.

Though initially designed to evaluate gross dexterity of cerebral palsy patients (Mathiowetz et al., 1985; Platz et al., 2005) the Box and Block Test has been adapted as a common

therapeutic and assessment tool for stroke rehabilitation. This test basically requires a patient to move as many wooden cubes ($2.5 \times 2.5 \times 2.5 \text{ cm}^3$) over a 15.2 cm high partition from one side of a wooden box to the other within 60 seconds. If more than one cube is being transported at the same time, it is counted as one. There is no accuracy requirement in placing the cube, but the fingers must cross the partition for the score to count. The number of successfully transported cubes is counted and compared to normative data (Mathiowetz et al., 1985) as a measure of gross dexterity.

The Jebsen-Taylor Hand Function Test (JHFT) (Jebsen et al., 1969) is a disability measure of hand function. Again, though not designed specifically for stroke, it has been commonly used in stroke rehabilitation as both a training and assessment tool. Unlike the Box and Block Test, the JHFT consists of seven functional tasks designed to assess the hand function. These include (i) writing, (ii) turning over 3×5 inch cards, (iii) picking up small common objects, (iv) simulated feeding, (v) stacking checkers, (vi) picking up large light objects and (vii) picking up large heavy objects (Jebsen et al., 1969). The amount of time required to complete these tasks is recorded and compared against normative data. Essentially, the Box and Block Test and JHFT are time-limited and time-based tests respectively that neither provide any measure of movement quality nor explain the underlying cause of motor dysfunction.

The Barthel Index (BI) is designed to measure disability in a global manner using real-life functional tasks. Shah et al (1989) modified this index to increase the level of sensitivity by replacing the original 3-point ordinal scale with a 5-point ordinal scale. This modified version is commonly known as the modified Barthel Index (MBI). This measure contains nine functional tasks, of which, four are related to UE functions such as (i) feeding, (ii) personal hygiene (grooming), (iii) dressing and (iv) bathing. Each of these tasks is scored against five levels of difficulties each describing the level of assistance required during performance of the tasks in an attempt to quantify functional recovery. As MBI focuses purely on the level of independence exhibited in completing the tasks, movement quality is not measured and, in fact, compensatory movements are accepted as part of the functional recovery.

Instead of solely assessing either impairment or disability, some scales like Action Research Arm Test (ARAT) (Lyle, 1981), Motor Assessment Scale (MAS) (Carr et al., 1985) and Wolf Motor Function Test (WMFT) (Wolf et al., 2005) assess both. ARAT consists of a mixture of simulated and real-life functional tasks grouped under four subscales namely (i) grasp, (ii)

grip, (iii) pinch and (iv) gross movement. The first three subscales assess disability via functional tasks such as reaching to grasp and transport objects, pouring of water and manipulation of small objects. The gross movement subscale gives a gross assessment of impairment. There are a total of nineteen test items, each of which is scored against a 4-point ordinal scale from '0' to '3'. ARAT focuses purely on task completion and movement quality is also not measured. The scoring is as follows (Lyle, 1981):

'3': Performs test normally

'2': Completes test, but takes abnormally long time or has great difficulty

'1': Performs test partially

'0': Can perform no part of test

The MAS is specifically designed to measure the progress of stroke patients (Carr et al., 1985). It consists of nine test items, of which, three are related to UE motor functions, namely (i) upper-arm function, (ii) hand movements and (iii) advanced hand activities. Each item is scored against a 7-point ordinal scale from '0' to '6'. Similar to the MBI, each score corresponds to a qualitative description of an activity to be performed. Hence, each item consists of six different activities, presumably with the most difficult one representing optimal motor behaviour scoring '6'. These activities and their associated scores are designed based on years of empirical observations made of large number of patients (Carr et al., 1985). They are aimed at assessing a wide range of motor capabilities from basic single joint movement such as shoulder girdle protraction, elbow flexion-extension, wrist extension, wrist radial deviation etc to complex multi-joints movements such as reach-to-grasp objects, tools manipulation, combing hair etc. For some activities, additional comments describing undesirable movements such as "do not allow pronation", "do not allow head to lower towards spoon" etc are attempts to monitor movement quality and compensation implicitly.

The WMFT has been used extensively as a stroke outcome measure especially for constraint induced movement therapy (CIMT) and chronic stroke patients (Wolf et al., 2005). It consists of fifteen test items to evaluate both UE impairment and disability via simulated and real-life tasks. Similar to MAS, the test items assess a wide range of motor capabilities from single joint movements to highly functional real-life movement such as reach-to-grasp (Wolf et al., 2001). The WMFT is a time-limited test in that each item is given a maximum of 120 seconds to complete. The scoring of task performance is similar to ARAT but a 6-point ordinal scale is used instead as follows (Wolf et al., 2005):

- ‘0’: Does not attempt with upper extremity (UE) being tested.
- ‘1’: UE being tested does not participate functionally; however, an attempt is made to use the UE. In unilateral tasks, the UE not being tested may be used to move the UE being tested.
- ‘2’: Does, but requires assistance of the UE not being tested for minor readjustments or change of position, or requires more than 2 attempts to complete, or accomplishes very slowly. In bilateral tasks, the UE being tested may serve only as a helper.
- ‘3’: Does, but movement is influenced to some degree by synergy or is performed slowly or with effort.
- ‘4’: Does; movement is close to normal but slightly slower; may lack precision, fine coordination, or fluidity.
- ‘5’: Does; movement appears to be normal.

Up to this point, it can be clearly observed that very little attention, if at all, is being paid to measuring movement quality in all the described outcome measures. Unfortunately, measurement of movement quality is rarely conducted objectively (Pomeroy et al., 2003). Bernhardt et al. (1998) and Pomeroy et al. (2003) show video recordings of patients to different therapists to have the patients’ motor performance assessed using a 100 mm vertical visual analogue scale. The authors note that while intra-therapist reliability is high, inter-therapist agreement is found to be low. This is believed to be due to therapists using different internal judgement models based on their personal definition of normative behaviour to assess quality of movement.

The inevitable side effect of not assessing movement quality properly is the emergence of compensatory movements. Current clinical assessment scales are not capable of distinguishing between compensation and true recovery (Levin et al., 2009; Krakauer, 2006) as they do not pay attention to the quality of task performance (Levin et al., 2009). Inappropriate compensation limits true recovery (Cirstea and Levin, 2000) and may promote learned non-use (negligence) that ultimately limits recovery of “normal” movement patterns (Roby-Brami, et al., 2003). Use of compensatory mechanisms is also found to correlate with poorer functional outcome as compared to true recovery of “normal” movement patterns (Roby-Brami, et al., 2003) as well as resulting in development of other orthopaedic problems due to “unnatural” joint positioning and coordination (Cirstea and Levin, 2000). Therefore, it is important to assess movement quality and detect use of inappropriate compensatory strategies as early as possible.

Movement quality can be measured in two ways. The first method is to compare the movement to a well defined norm. Degree of deviation from this norm can then be used as a measure of quality. Yozbatiran et al. (2007) propose a standardized way to conduct ARAT by defining time constraints for task completion as well as providing qualitative kinematics descriptions of desired movement pattern. In this way, in addition to task completion, score is awarded based on exhibition of expected normal movement mechanics. The second method involves defining explicitly the sets of undesirable compensatory movements that can be expected. In this case, the amount of compensatory movements exhibited is used as a measure of movement quality. To better assess quality of reaching and grasping in stroke patients with hemiparesis, Levin et al. (2004) develop the Reaching Performance Scale (RPS) that explicitly detect compensatory movements.

However, use of qualitative descriptors of expected outcomes in all the aforementioned scales, regardless of impairment or disability measure, introduces a high degree of subjectivity. In FMA, descriptors such as “faultlessly”, “smoothly”, “without jerk”, etc are used. In MBI, under personal hygiene task, descriptors that correspond to scores of ‘3’, ‘4’ and ‘5’ are “some assistance”, “minimal assistance” and “can wash his/her hands and face, comb hair, clean teeth and shave” respectively. In the RPS, “small displacement”, “fluid and smooth”, “adequate”, etc are used to describe optimal performance with no compensation. Though qualitative kinematics descriptions of desired movement pattern is provided in the standardized ARAT (Yozbatiran et al., 2007), these lack accuracy in terms of defining what is normal. For instance, it is stated that the elbow is expected to be flexed when first grasping an object but the amount of normal flexion to be expected is not stated. All these undoubtedly leave room for arbitrary interpretations of what constitute a normal movement.

Furthermore, ordinal scale may not have the necessary resolution to detect small but significant changes (Ashford et al., 2008; Coderre et al., 2010; McCrea et al., 2002; Nowak, 2008). The FMA for instance is not recommended for mild stroke patient because of ceiling effect (Gladstone et al., 2002). Sanford et al. (1993) note that a change of 10 points on FMA on the same patients, when assessed by two different therapists on two different occasions may not be sufficient to conclude if a real change due to treatment has occurred. More importantly, as recovery is a continuous process, rating scales should generate interval level measurements which will then ensure that differences in points have the same meanings

(Hobart et al., 2007). For example, two patients who showed a 1 point improvement in their MAS scores may not have improved in their actual functional ability to the same degree. Furthermore, Hobart et al. (2007) comment that as the confidence intervals around the ordinal score are too wide for an individual, ordinal scores are only suitable for group-level comparisons. This implies that ordinal scales may not be clinically useful where treatment effects are needed to be determined on an individual basis.

In concluding this section of literature review, the following main points should be noted:

- 1) Use of qualitative descriptors to score motor performance and assess movement quality is a common practice in most outcome measures. However, interpretation of these descriptors can be highly subjective.
- 2) Most, if not all, common outcome measures are ordinal scales. Such scales lack the necessary resolution to track small but significant changes and do not capture the continuous process of recovery adequately.
- 3) There is clearly a lack of consensus over the test items used in the various outcome measures. Frequently, these are selected based on empirical experience of those who developed the scales. Despite this, it can be observed that reach-to-grasp is a functional activity that is common to all these scales.

2.2 Review on motor control theories and explore existence of normal movement for reach-to-grasp

As stated in Section 1.2, this study aims to establish normative kinematic(s) of a reach-to-grasp task. Thus, the objective of this section is to review some important motor control theories to explore if it is reasonable to hypothesize that normal movement exists for a reach-to-grasp task.

The human body is endowed with far more degrees of freedom than are necessary to perform physical movements in a three dimensional world. Ever since the Russian physiologist, Nicolai Bernstein, raised this degrees of freedom problem, human movement scientists have proposed many motor control theories attempting to explain how the CNS plans and controls movements.

The Motor Program theory is one of the first motor control theories that is proposed to explain how the CNS produces movement. This theory proposes that all movements are centrally

structured with minimal role for sensory feedback (Schmidt & Lee, 2005) and is mainly supported by three lines of evidences:

- (i) EMG experiments showed that feedback processing is slow, thus implying that at least part of the movement must be pre-planned by a motor program.
- (ii) Reaction times increase with task complexity indicating that a response-programming stage requires more time to plan. This indicates that movements are planned in advance.
- (iii) Deafferentation studies show that even without feedback from moving limb, movement can still be initiated.

However, if feedback is not incorporated in motor control, each unique movement has to be completely specified by a unique motor program. This implies that our CNS (i) must have an infinite amount of storage space, and (ii) lacks the ability to learn novel movements (Schmidt & Lee, 2005). These two limitations led to the proposal of a Generalized Motor Programs (GMP) theory. The GMP proposes that each class of actions is specified by a unique template of activities and a set of invariant features. By taking into consideration task demands, a class of actions is selected and a set of parameters is specified so as to define how the template of activities will be activated. Schmidt and Lee (2005) state three such parameters as (i) overall duration parameter, (ii) overall force parameter and (iii) muscle-selection parameter. By adjusting these three parameters, different movement outcomes can be produced, while retaining invariant features unique to individuals, for the same class of actions. These invariant features are (i) relative timing, (ii) relative force productions among contractions and (iii) sequence of muscles activation (Schmidt & Lee, 2005). Consequently, variations in movement outcome are considered to be results of errors (Stergiou & Decker, 2011) in the specifications of these parameters. However, Schmidt and Lee (2005) noted that the GMP is more suited for discrete tasks, especially those that rely on advance planning for successful execution, than continuous tasks.

The Dynamical Systems Theory (DST) of motor control proposes that movement strategies are not specified or programmed, but rather motor behaviour emerges from the interaction of many systems (Mathiowetz & Bass-Haugen, 2008). The central idea of DST is that the neuromuscular system self-organises by changing states over time in search for the most stable solution, also known as the attractor state (Hamil et al., 2006; Mathiowetz & Bass-Haugen, 2008; Schmidt & Lee, 2005; Stergiou & Decker, 2011). This process of self-organisation is prompted when changes in control parameters' values cross critical thresholds

(Kurz & Stergiou, 2004). These control parameters can be either internal or external. Internal control parameters include neuromuscular dysfunction and external control parameters include environmental obstacles (Kurz & Stergiou, 2004). Under the DST theoretical framework, movement variability is viewed as a means by which the neuromuscular system explores different control strategies so long as the task objectives are not compromised (Hamil et al., 2006). In other words, a healthy neuromuscular system is viewed to be sufficiently stable to produce a consistent desired movement outcome while at the same time is sufficiently flexible to respond to a dynamically changing environment (Bass-Haugen, Mathiowetz & Flinn, 2008). In fact, it is believed that it is the ability of the neuromuscular system to reorganise itself in response to environmental challenges that contributes to the central nervous system (CNS) plasticity in reorganising itself after stroke (Sabari, 2008). DST overcomes the two major limitations of GMP by (i) not requiring storage space for any motor program and (ii) enabling learning of novel tasks through behavioural transitions in search for new stable solutions (Stergiou & Decker, 2011). It also offers a sound explanation to the observation that two fingers (one on each hand) performing abduction-adduction movements in anti-phase sequence transit to in-phase sequence when the speed increases (Kelso & Schoner, 1988). Coker (2009) notes that this phenomenon is consistent with the DST perspective in that a change in speed constraint induces a self-organisation of the neuromuscular system resulting in the emergent of a new behaviour. However, Schmidt & Lee (2005) note that DST is more suited for continuous cyclical tasks as it fails to explain observations that when limb is immobilised, electromyograph (EMG) pattern of an intended discrete action unfolds almost without interruption.

Closely related to the DST, the ecological approach to motor control proposes that a direct relationship exists between perception and action (Coker, 2009; Rose & Christina, 2006). The continuous interaction between perception and action is believed to be a circular one (Coker, 2009) and visual information plays an important role in the determination of environmental properties, known as affordances, that drive the nature of the final action (Rose & Christina, 2006). It is also believed that visual information regarding the environment can be directly extracted without higher order cognitive processes (Rose & Christina, 2006). This in turn allows for continuous adjustments of movements in dynamic situations, especially those lasting more than 100 msec (Rose & Christina, 2006). In particular, this assumption that affordances can be directly perceived supports the hypothesis that an optical variable,

known as tau, which provides an estimate of time-to-contact of a target, guides actions in different movement settings (Rose & Christina, 2006; Williams, Davids & Williams, 1999).

The uncontrolled manifold (UCM) hypothesis is proposed by Scholz and Schoner (1999) to explain and explore how the CNS manages the problem of redundancy in complex multi-joint human movements. Similar to the DST, the UCM considers movement variability to be an inherent component of all human movement. The UCM introduces the concept of “good” and “bad” variability. The “good” variability refers to the variability that does not affect the outcome of a task and the “bad” variability refers to the variability that adversely affects the outcome of a task. In other words, excessive amount of variance in parameters that are crucial to the successful accomplishment of a given task is considered as “bad” and needs to be tightly controlled. Hence, the UCM hypothesis suggests that the CNS controls only those parameters that are crucial to the successful accomplishment of a given task. The controlled parameters will exhibit lower degree of variability than those uncontrolled parameters that have little or no effect on the outcome of the task. In this way, UCM has been shown to be useful in discovering coordination strategies for several motor tasks (Stergiou & Decker, 2011). Taking a similar view of movement variability, Todorov and Jordan (2002) propose that the CNS motor control functions can be modelled based on the principles of optimal feedback control. Similar to the UCM, the CNS is believed to function based on the minimal intervention principle and controls only those parameters that are critical to task accomplishment. Both the UCM hypothesis and the optimal feedback controller theory are essentially useful tools to discover coordination strategy and hence are particularly useful for analysis of skilled performance of well-practiced tasks without considering the learning and adaption processes that lead to such skilled performance (Todorov & Jordan, 2002).

From the above discussions, it can be observed that much of the studies of human motor control are underpinned by the notion that movement variability needs to be minimised for smooth execution of a motor task. However, Stergiou and Decker (2011) propose an intriguing concept that all skilled performances of human movements incorporate movement outcome variability at an optimal level. Importantly, an optimal level of movement variability reflects the adaptability of the underlying control system (Stergiou & Decker, 2011) which is indicative of a healthy biological system (Harbourne & Stergiou, 2009). This concept of optimal movement variance is analogous to the concept of homeostasis in human physiology which states that the human body is in a state of dynamic equilibrium to keep a relatively

stable internal condition even when the external environment is changing. Stergiou and Decker (2011) and Harbourne and Stergiou (2009) further argue that temporal variance in human movement is chaotic in nature and subsequently cite various studies that demonstrate the use of nonlinear dynamic measures such as largest Lyapunov exponent (LyE) and approximate entropy (ApEn) to successfully detect significant differences in the structure of temporal variance between normal and pathological movements. Therefore, in the study of a movement task, it is highly recommended that both amplitude variations of movement parameters and temporal organisation of these variations be measured to give a more comprehensive description (Stergiou & Decker, 2011). However, Harbourne and Stergiou (2009) noted that nonlinear dynamic measures require lengthy time series and multiple repetitions of a movement, hence, limiting their usage in clinical settings especially on patients who cannot tolerate lengthy assessment procedures.

Until now, various theories and models of motor control have been discussed in order to explore if it is reasonable to hypothesize that normal movement exists for a reach-to-grasp task. In this study, the selected reach-to-grasp task is a familiar and well-trained task to all subjects (refer to Chapter 3 for a detailed description). Hence, the following discussions on the existence of normal movement shall be confined to this context.

The human upper extremity has much more degree of freedom than is necessary to function in a three dimensional world (Bernstein, 1967), resulting in indeterminacy of movements. Physically, this means that there are an infinite number of trajectories to transport the end-effector (hand) from one point to another. In terms of biomechanics, this simply translates to mean that there are an infinite number of combinations of segment or joint angles (coordination between multiple segments or joints) that result in the same final position of an end-effector (hand). As a result, it may have seemed reasonable to assume that normal reach-to-grasp movements, in general, do not exist. The following paragraphs will explore if this is a fair and valid assumption on the individual and group levels.

Just because the human upper extremity has an excess number of degree of freedom to perform a reach-to-grasp task does not imply that the CNS will necessarily use or even explore all of them. This is especially so for a familiar and well-trained task which the CNS is no longer expected to be exploring and learning the best movement solution. According to DST, the notion of stable solution in a fixed context implies that a similar pattern of activation

is adopted when all other variables are held constant. Similarly, under the ecological approach, if affordances (environmental properties) remain relatively constant, it is conceivable that a relatively consistent action output is maintained. In other words, it is highly likely that normal movement of a well learnt task within a stable environmental context and task goal exists, at least on an individual level. Hence, it is conceivable that while the number of trajectories and inter-segmental or inter-joints coordination options for a familiar and well-trained reach-to-grasp task are infinite, they are in fact bounded. That is, for each movement parameter, there exists a proper infinite subset that defines normal movement of a well learnt task. This concept of bounded infinite set is best illustrated by a mathematical analogy in the example of a set of real number defined on a closed interval of $[a, b]$. This set of real number is bounded between values a and b but contains as infinitely many real numbers as the entire set of real numbers. In the context of the reach-to-grasp task, the bound of a subset of selected hand trajectories is likely to be specified by task goal as hypothesized by the UCM and the optimal feedback controller theory. Furthermore, according to the GMP theory, it appears that the concepts of “template of activities” and “invariant features” support the hypothesis that normal movement exists, at least on an individual level, for a given task.

For a given familiar well-practiced motor task, both UCM and optimal feedback controller theory necessarily assume the existence of a common coordination strategy among different individuals. Based on the UCM, by identifying the same set of movement parameters that are tightly controlled by the CNS across different subjects, the control strategy for a motor task can be inferred. Similarly, the optimal movement variability model uses different normal subjects to define the optimal level of movement variability hence assuming that a normal variance structure exists among a group of normal individuals. Latash (2008) noted that despite a big spectrum of movement patterns among a group of individuals performing the same motor task, there exist common features that are produced by most persons without movement impairment. These common features are believed to be produced based on a set of rules known as CNS priorities that are assumed to be common to all normal average people without highly specialized motor skills who also qualify as control subjects in human movement studies (Latash, 2008). These CNS priorities are believed to be different for highly skilled and clumsy people who exhibit different movement patterns that occupy the two extreme ends of the movement pattern spectrum (Latash, 2008). To a large extent, this concept of CNS priorities may explain how the CNS selects the set of crucial movement parameters to be controlled as proposed by the UCM (Scholz & Schoner, 1999) and optimal

feedback controller theory (Todorov & Jordan, 2002) as well as how an optimal level of movement variability (Stergiou & Decker, 2011) is determined among different individuals. In this sense, a group of normal average people will share similar movement patterns that are bounded, when performing the same motor task. Hence, the working principles of these theories provide support for the existence of normal reach-to-grasp movement on a group level. Therefore, the challenge now is to explore the possibility of providing a kinematic description for a normal, familiar and well-trained reach-to-grasp movement.

In concluding this section of literature review, the following main points should be noted:

- 1) Movement pattern variability is an inherent and important feature of a healthy CNS that is highly adaptable and capable of learning new motor skills.
- 2) Control rules may exist in the form of deciding the set of movement parameters to control (relative to task goal) and determining the optimal levels of variability for these parameters.
- 3) The working principles of various motor control theories support the existence of normal movement for a familiar and well-trained task and the greatest challenge remains in finding the appropriate kinematic description for such normal movement.

2.3 Review on UE kinematic motion analyses

Quantitative biomechanical studies of human movement have contributed towards much of our current understanding and knowledge of human motor learning and control. 3D kinematic analysis of gait dominated much of the early researches in this area. In gait analysis, normative kinematics, kinetics and electromyographic data are often used as references against which experimental results can be compared (Thompson, 2006).

Deviations from the normative values are often used as an indication of abnormal gait and rehabilitation can then be tailored to target specific areas with large deviations. Gait analysis has been successfully integrated with clinical assessment (Rau et al., 2000). Surgical planning guided by 3D gait analysis resulted in better postoperative outcomes in patients with cerebral palsy (de Moraes Filho et al., 2008). Such successes formed a basis for an evolution of modelling in recent years, moving from the lower body to the upper body (Slavens, 2008).

Development of clinically useful UE kinematic models (Hingtgen et al., 2006; Rau et al., 2000; Williams et al., 2006), which may be used for quantification of progression of stroke recovery, promotes the use of kinematic outcome measures to determine efficacy of

rehabilitation. Meanwhile, advances in technologies such as motion capture and robotics have made measurement of kinematic parameters easily available to researchers and clinicians. As a result, different combinations of kinematic parameters have been proposed to quantify UE functional performance. This is a distinct advantage of kinematic motion analysis as it allows for a complex movement to be analysed at its subcomponent levels. However, kinematic motion analysis should be used in conjunction with clinical assessment as the clinical relevance of the changes observed in many of the kinematic parameters have yet to be ascertained (Nowak, 2008).

Recent efforts have been directed towards the determination of kinematics during UE functional activities in normal population. Such normative kinematics will be useful in elucidating the motor control strategies of UE functional tasks as well as form the basis against which pathological movement can be compared and assessed (Petuskey et al., 2007; van Andel et al., 2008). In an attempt to create a standardized protocol for clinical evaluation of the whole UE, simulated functional tasks such as hand to the contralateral shoulder, hand to mouth/drinking, combing hair, hand to back pocket, high reach above head, forward reach to receive change, wave with arm at side, page turning and reach-to-grasp objects have been used (Butler et al., 2010; Coluccini et al., 2007; Murgia et al., 2010; Petuskey et al., 2007; van Andel et al., 2008). Normative values of kinematic parameters such as task duration as well as joint angles of the wrist, elbow, shoulder and scapula are reported in these studies.

In assessing the repeatability of upper and lower limb 3D kinematics in children with hemiplegic cerebral palsy during hand-to-mouth, hand-to-head and 10-m gait test, Mackey et al. (2005) find that 3D kinematic analysis of movements of the hemiplegic upper and lower limb have moderate to good repeatability. In particular, sagittal plane kinematics is most reliable. Similarly, Wagner et al. (2008) note that peak hand velocity, endpoint error, reach extent, maximum shoulder flexion range of motion and minimum elbow extension range of motion are reliable measures of motor performance in stroke patients with hemiparesis performing a reaching task. However, peak hand velocity, time to peak hand velocity and movement time may be less sensitive to changes as their percentage minimal detectable change are calculated to be more than 50%. In other words, these parameters have to change more than 50% for the change to be regarded as real. In another study on the kinematic analysis of reaching and grasping in children with hemiplegic cerebral palsy, Rönnqvist and Rösblad (2007) conclude that movement duration, total movement distance, number of

movement units, straightness of the reach trajectory, maximum aperture, placement of the max aperture in percent of the total reach duration, grip aperture at hand-object contact and time taken to establishing grasp are kinematic parameters that are sensitive to the different levels of functional impairment.

Kinematic motion analyses have been shown to have high correlation with some current assessment scales. Kamper et al. (2002) define five reaching parameters namely, fraction of reach, path length ratio, peak speed difference, number of speed peaks (smoothness) and movement direction variability to quantify reaching performance of chronic hemiparetic stroke patients. It is reported that these parameters are highly significantly linearly related to the scores on the Chedoke-McMaster Stroke Assessment (CMSA) scale. Similarly, Coderre et al. (2010) use a robotic exoskeleton to measure twelve kinematic parameters and found good correlations between four of these parameters with the CMSA scale for scores lesser than '7'. Also using a robotic manipulator, Bosecker et al. (2010) derived twenty kinematic and kinetic parameters and constructed a linear relationship between the UE FMA scores and a subset of these parameters via backward regression analyses. Murphy et al. (2010) determine that movement smoothness, movement time and peak elbow angular velocity are capable of discriminating between mild and moderate impairment levels after stroke as classified by the UE FMA.

In addition, other studies have demonstrated that kinematic analyses are more sensitive than current assessment scales. Coderre et al. (2010) report that kinematic analyses are able to correctly detect movement deficits in some stroke patients that had otherwise been wrongly classified as being normal (score '7') on the CMSA scale. Subramanian et al. (2010) demonstrate that trunk displacement, shoulder flexion, shoulder horizontal adduction and elbow extension are valid measures of arm motor impairment with the ability to distinguish between motor recovery and compensation for a reach-to-grasp task. These parameters are found to be more sensitive than UE FMA in identifying UE deficit, even in patients with high level of recovery.

Due largely to its high level of reliability and sensitivity, kinematic analyses have been used in determining treatment effects of constraint induced movement therapy (CIMT) (Caimmi et al., 2008; Wu et al., 2007). Wu et al. (2007) recommend that kinematic analyses be used to complement clinical assessment in order to provide insights into improvement in motor

control strategies. Similarly, Caimmi et al. (2008) find kinematic analyses to be satisfactorily reliable and sufficiently sensitive to monitor motor recovery as well as to study the mechanism resulting in functional recovery. De Jong, Schefer and Lang (2012) investigate the effects of moving as fast as possible for a reach-grasp-lift movement with stroke patients and find that movement quality (as quantified by reach path ratio, peak aperture, aperture path ratio and peak grip force) improves with an increase in movement speed. This illustrates the usefulness of kinematic parameters in evaluating efficacy of treatment methods.

Up to this point, it is clear that there is no consensus over the set of kinematic parameters to be used in characterizing and assessing normal and pathological reach-to-grasp tasks respectively. This choice, if not made randomly or out of convenience, should be based on the understanding of how our CNS plans and execute UE movements. Currently, it is hypothesized that this is accomplished based on either an intrinsic (body-centered or joint) or extrinsic (fixation-centered or end-effector) coordinate reference frame. Though the issue on which reference frame the CNS plans and executes UE movements remains an open research question (Shadmehr & Wise, 2005), report on healthy growing children exhibiting better control over hand trajectory earlier than interjoint coordination in reach-to-grasp gives support for an end-effector reference frame (Schneiberg et al., 2002). Over the years, others have reported a typical bell-shaped, though not necessarily symmetrical, end-effector tangential velocity (TVel) profile for horizontal reaching and reach-to-grasp movements (Flash & Hogan, 1985; Morasso, 1981; Nagasaki, 1989; Suzuki et al., 1997) resulting in an almost straight hand path (Flash & Hogan, 1985). These are often taken to imply that movements are planned in hand space (Winstein, Wing & Whittall, 2003).

Neuroscience and neurophysiological studies of reaching and pointing also seem to provide stronger evidence in favour of an extrinsic coordinate frame (Shadmehr & Wise, 2005; Winstein et al., 2003). Flanagan and Rao (1995) investigate if the straight hand path achieved during horizontal reaching is a result of perception or movement production. In their experiment, participants are required to move a cursor on a computer monitor to various targets under two experimental conditions. The cursor's 2D location corresponded to either (i) the hand's position (hand-space) or (ii) the shoulder (ordinate) and elbow (abscissa) angles (joint-space). In both conditions, the participants could not see their hands. Expectedly, participants had no problem with the hand-space condition and move the cursor to the targets in a straight path with corresponding straight line motion of the hand. On the other hand, only

after extensive practices, participants are also able to achieve the same result in the joint-space condition but in this case, the actual hand path is curved. Hence, the authors conclude that horizontal reaching is executed so that the end-effector achieved a straight path in visually perceived space.

Bueno et al (2002) arguably provide the strongest piece of neurophysiological evidence that reaching is planned in the extrinsic (fixation-centered) coordinate frame. In their experiment with monkey, activity from a single neuron in the posterior parietal cortex (PPC) area 5 is recorded as the monkey performed an unconstrained reaching task. Referring to Figure 2.2, comparing Condition 1 and 4, the absolute positions of the fixation point (filled circle), hand location (unfilled circle) and target location (arrow) had all been shifted one unit square to the right while keeping their relative locations constant. In doing so, although the joint angles in the UE had changed, the neuronal activities as shown in the spike density histograms remained largely unaffected. If the intrinsic (joint) coordinate frame had been used, this change in joint angles would have resulted in different neuronal discharges. Similar conclusion can be drawn from comparing Condition 2 and 3.

Figure 2.2: Neurophysiological evidence suggesting that reaching is planned in the extrinsic (fixation-centered) coordinate frame. Note the similarity in spike density histograms (measure single neuron activity in PPC area 5) between Condition 1 and 4 as well as between Condition 2 and 3 when the relative positions of the hand position (unfilled circle), target location (arrow) and fixation point (filled circle) remain unchanged. Source: Bueno et al (2002).

Shadmehr and Wise (2005) suggest the following biological advantages of adopting an extrinsic (fixation-centered) coordinate frame:

- i. Targets for reaching and pointing are represented in the same coordinate system as that used for planning eye movements to the same targets.
- ii. Vision provides the most accurate spatial information to the primates.
- iii. By maintaining the same coordinate system as vision, it facilitates easier calibration and error detection.

From a motor control perspective, the DST and ecological approach both propose a strong influence of the environment (task constraints, affordances, etc.) on the planning and control of movements (Section 2.2). In particular, visual perception is believed to play an important role in shaping actions (Rose & Christina, 2006). In addition, the hypothesis that an optical variable which estimates the time-to-contact of a target (commonly referred to as tau) exists, is supported by mathematical modelling, computer simulations and experimental evidences (Rose & Christina, 2006; Williams et al., 1999). The existence of tau in turns gives support for an end-effector reference frame.

The hypothesis that the CNS plans a reach-to-grasp movement in hand space has implications on the conduct of clinical assessment of UE functions. Under this hypothesis, deviation from a straight hand path is often taken as a classic sign of ataxia (Winstein et al., 2003). Center out reaching task might also be developed for UE assessment, in which departures from straight -line paths are indicative of interjoint coordination problems (Winstein et al., 2003). Besides coordination, movement smoothness of the end-effector (hand) is another parameter that is commonly used in the quantification of the quality of UE movements. A decrease in movement smoothness is quantified by an increase in the number of submovements. These submovements are extracted from the end-effector (hand) TVel profile using a variety of algorithms. The stochastic optimized submovement model (Meyer et al., 1988) is one of the earlier efforts to discover submovements by detecting zero crossings in the hand TVel, acceleration and jerk profiles. Flash & Hogan (1985) noted that the hand TVel profile of a horizontal reaching movement resembles a symmetrical bell-shaped curve and proposed a minimum jerk model to explain this phenomenon. Complementing this work, Krebs et al. (1999) obtain irregular hand TVel profiles from stroke patients and discover that it is possible to decompose these profiles into summations of individual bell-shaped TVel profiles which they believe to be the fundamental building blocks of complex motions. However, Plamondon (1995) proposes that hand TVel profiles may not be symmetrical as predicted by

the minimum jerk model. For rapid hand movement, Plamondon (1995) proposes that the hand TVel profile is better represented by a log-normal function and this can be further decomposed into a pair of agonist-antagonist submovement log-normal functions. By relaxing the criteria for symmetry of submovement TVel profiles, Rohrer and Hogan (2003, 2006) and Fishbach et al. (2005) propose new algorithms to decompose a hand TVel profile into its submovement components so as to provide a more accurate measure of movement smoothness.

From the foregoing discussion, it can be concluded that the hand TVel profile plays an important role in quantifying the movement quality of a UE motor task. Importantly, the smoothness of the hand TVel profile is found to be capable of discriminating between different impairment levels of stroke patients (Murphy et al., 2010; Kamper et al., 2002). In addition, smoothness of the hand TVel profile has also been observed to increase, as indicated by a decrease in the number of submovements, as patients with stroke recover UE function (Rohrer et al., 2002, 2004). In other words, the hand TVel profile exhibits detectable changes in the case of pathological reach-to-grasp movements. This implies that the hand transport TVel satisfies one of the criteria defined in Section 1.3 (i) to be an adequate kinematic parameter to characterize a reach-to-grasp task. In order for the hand TVel to be considered an adequate kinematic parameter, it is required to satisfy one other criterion, that is, to have at least one invariant feature.

Morasso (1981) discovers an important invariant feature of the hand TVel profile of a reaching task. When subjects are instructed to reach for objects located at different locations, Morasso (1981) notes that the joint angular curves vary considerably but the hand TVel profiles preserve their single-peak and bell-shaped characteristics. This experimental observation is further supported by optimization theories, such as minimum jerk hypothesis (Flash & Hogan, 1985) and minimum torque change model (Uno, Kawato & Suzuki, 1989), that are able to reproduce bell-shaped hand TVel profiles. Under the minimum jerk hypothesis, it is believed that smooth coordinated movements are produced by minimizing the amount of jerk. The minimum torque-change model, on the other hand, proposes that the CNS aims to minimize the total change in torque across all joints. Pigeon, Bortolami and Lackner (2003) conclude that under the assumption of an extrinsic coordinate frame, the hand TVel profile of a turn-and-reach movement is found to be bell-shaped and this shape is invariant for both fast and slow movements. Guigon, Baraduc and Desmurget (2007) make

similar observation based on their newly proposed motor control model. It is proposed that motor control is governed by four principles, (i) *separation* in planning of static and dynamic forces, (ii) *optimal feedback control* of dynamic forces, (iii) *maximum efficiency* in control of movement parameters and (iv) *constant effort* for all movements obeying a given set of instructions. Under this model, the invariant bell-shaped hand TVel profile for point-to-point movements appears to be an emergent property which scales in time and magnitude depending on different movement requirements. Hence, it can be concluded that the hand transport TVel of a reach-to-grasp movement is invariant in shape.

As the hand transport TVel is found to fully satisfy the adequacy criteria set in Section 1.3 (i), it is deemed to be an adequate kinematic parameter to characterize a reach-to-grasp movement. From this perspective, therefore, movement quality shall be defined in terms of the degree of agreement with normative hand transport TVel amplitude behavior which is to be established in Chapter 6 and 7 of this thesis. A practical advantage of assessing the movement quality of a reach-to-grasp task in this manner is that the hand transport TVel is easily measurable in the clinic. This is an important consideration as it increases the chance of an assessment protocol to be implemented clinically.

In concluding this section of literature review, the following main points should be noted:

- 1) Kinematic motion analyses have been shown to be sufficiently reliable, valid, responsive and sensitive to be used as an objective assessment tool in stroke UE rehabilitation.
- 2) In some studies, kinematic motion analyses have even been demonstrated to be more sensitive than current clinical assessment scales especially in detecting motor deficits in mild or highly recovered stroke patients.
- 3) There is clearly a lack of consensus over the set of kinematic parameters to be used. Empirical and neurophysiological evidences suggest that our CNS plans and executes reaching and pointing in the hand space. Since the hand transport TVel has an invariant shape and is sensitive to pathological reach-to-grasp, it is likely to be most useful for the purpose of characterizing normal reach-to-grasp task. Furthermore, hand transport TVel is easily measurable clinically.

2.4 Review on time normalization of UE kinematic curve

In order for the following review to be meaningful and taken in the correct context, it is now appropriate to describe briefly the reach-to-grasp task that normative kinematic will be constructed for in the current study. Like many common UE assessment procedures, the hand starts in a pronated position with the thumb touching the side of the index finger and the rest of the fingers closed up together. This starting position resembles a person holding a computer mouse on a horizontal surface. The task to be performed involves reaching medially to grasp an object and transport it to a target location before returning to the starting position. In this study, the reach-to-grasp portion of the entire task shall be the focus. In the process of reaching to grasp the object, the three main movement components are hand transport, forearm supination (orientation) and grasping. More detail regarding the experimental protocol is described in section 3.2.

As is concluded based on literature review in Section 2.3, this study shall focus on investigating how the hand transport TVel can be used to characterize and represent the reach-to-grasp task, described above, in a normal population. Many specific landmark kinematic parameters such as peak TVel amplitude, time to peak TVel, movement duration, peak acceleration, time to peak acceleration, etc have been derived from hand transport TVel and used to characterize the hand transport component. However, the use of such specific kinematic landmark parameters only provides a microscopic view of the entire kinematic curve (Chau et al., 2005). Furthermore, two TVel curves can have similar peak TVel amplitude and time to peak TVel but differ in their shapes. From the perspective of establishing normative kinematic of reach-to-grasp against which pathological movements can be compared and assessed, specific kinematic landmark parameters do not seem likely to be able to provide sufficient kinematic information for a comprehensive and accurate assessment over the entire duration of the movement. Hence, Chau et al. (2005) propose that kinematic curves should be compared as coherent entities to provide a more complete picture of the movement under investigation. The authors illustrated the use of the adaptive Neyman test (Fan & Lin, 1998) to compare the entire time series of ankle angle during gait of patients wearing two different types of prosthesis as well as patients who have undergone ankle surgery. It is then recommended that such full curve comparison and analysis for kinematic data be performed to supplement specific kinematic landmarks testing.

The main challenge in establishing normative kinematic using the entire kinematic time series curve is time normalization. Time normalization is necessary for aligning curves from repeated measures of a subject or group so as to minimize or remove temporal variations prior to the calculation of an ensemble mean curve that represents the ‘average’ performance of an individual subject or group for a particular task. Linear time normalization method which defines start of a task as 0% and the end of the task as 100% is often used. However, this is generally not applicable to UE tasks as UE movements are often non-periodic and noncyclical (Rau et al., 2000). Thies et al. (2009) illustrate in Figure 2.3 that linear time normalization for UE tasks introduced the risk of aligning trials inappropriately. This in turn results in inaccurate level of inter-trials variance and also increases the chance of losing or falsely creating important kinematic landmarks in the process of constructing an ensemble mean curve. Hence, accuracy of an ensemble mean kinematic curve depends directly on the time normalization of individual trial curves.

Figure 2.3: Inadequacy of linear time normalization. Acceleration curves for Trial A and B are subjected to linear time normalization by using the movement onset and offset times. Note that the normalized curves clearly exhibit regions of mismatching important events which will in turn increase the inter-trial variability inaccurately. Source: Thies et al (2009).

In a set of curves, there are two sources of variability namely, amplitude variability and phase variability. In the context of this study, phase variability is more aptly referred to as temporal variability. Curve registration aims to remove or minimize temporal variability by seeking to

align all curves in a set according to a common template curve. The continuous functions that perform the registration for the individual curves are commonly referred to as warping functions. The need for curve registration to be performed on a set of curves is justified when the physical time does not adequately account for an underlying dynamic process of the system under investigation (Ramsay & Silverman, 2006). Recognising the importance of accounting for the underlying biological process of human movements, various studies have applied curve registration techniques on the investigations of gait (Chau et al., 2005; Sadeghi et al., 2000), chewing (Crane et al., 2010) and sit-to-stand (Page et al., 2006), just to list a few.

Sadeghi et al. (2000) apply curve registration to normalize the time in the muscle power curves of the hip, knee and ankle in the sagittal, frontal and transverse planes during gait. In their procedure, the ensemble mean curve of the set of unregistered curves is used as the initial template curve. In addition to movement onset and offset times, three additional landmarks are selected from inflection points and zero-crossings of this template curve. Warping functions for individual curves are constructed by piecewise linear interpolations based on these five landmarks. Finally, each curve is 'time-warped' via their respective warping function to achieve a set of registered curves. The final registered ensemble mean curve is then constructed based on this set of registered curves. When the mean root mean square (RMS) value calculated between the unregistered ensemble mean curve and the individual unregistered curves (UnregRMS) is compared with the mean RMS value calculated between the registered ensemble mean curve and the individual registered curves (RegRMS), it is noted that RegRMS decreased by an average of 13.6%. It is thus concluded that curve registration reduced variability in the muscle power curves in that study. However, there are two main shortcomings in this study. Firstly, the unregistered ensemble mean curve might have lost or falsely created landmarks due to inter-trial variance. Hence, landmark identification based on the unregistered ensemble mean curve which is used as the template curve could be erroneous. Secondly, the rationale for selecting the three additional landmarks is not explained.

On the other hand, Crane et al. (2010) and Page et al. (2006) apply the continuous monotone registration method (Ramsay & Silverman, 2006) to perform time normalization on chewing and sit-to-stand trials respectively. Like the technique described in Sadeghi et al. (2000) study, the continuous monotone registration method uses the unregistered ensemble mean

curve as the template curve. The main difference and advantage, however, is that it does not require landmark identification. In fact, this method is developed precisely to circumvent the problems and difficulties encountered in identifying landmarks accurately and meaningfully. Suffice to state that warping functions are constructed using a linear combination of B-spline basis functions (Gervini & Gasser, 2004; Page et al., 2006; Ramsay & Silverman, 2006). However, this technique tends to over-register the curves when too many basis functions are used (Gervini & Gasser, 2004). Nevertheless, Crane et al. (2010) report an 18.6% to 20.3% decrease in inter-subject variability while Page et al. (2006) report a decrease of intra-subject variability of as much as 59%.

Despite various curve registration techniques being proposed over the last decade, landmark registration is still widely accepted as the golden standard in curve registration (Gervini & Gasser, 2004; Ramsay & Silverman, 2006). It is likely that the method proposed by Sadeghi et al. (2000) is based on landmark registration. Landmark registration consists of two main steps namely (i) landmarks identification and (ii) warping function construction. Central to the procedure of landmark registration is landmark identification. Gasser and Kneip (1995) propose to search for consistent occurrences on all the curves under investigation which are termed “structural points”. These can be, but not limited to be, the local extremas and inflection points on the curves. The frequencies of these structural points along the abscissa are known as “structural intensities” which are determined by means of kernel density estimators (Gasser & Kneip, 1995). Referring to the structural intensity curve for boys (dotted line) in Figure 2.4(b), the locations, along the abscissa, of the two maximas on this curve represent the two locations where high frequencies of acceleration maximas are occurring among the individual acceleration curves (dotted) in Figure 2.4(a). These two time points can then be used as landmarks to construct warping function for each acceleration curve. That is, the individual acceleration curve will seek a continuous warping function that will align its maximas corresponding to these two landmarks temporally.

Figure 2.4: Structural intensities. (a) Acceleration of trunk bone length growth for 5 boys (dotted) and 5 girls (solid). (b) Structural intensities of local acceleration maximas for 120 boys (dotted) and 112 girls (solid) based on similar sets of acceleration curves shown in (a). Source: modified from Gasser & Kneip (1995).

The main advantage of the landmark registration method is that it does not use an unregistered ensemble mean curve as the template curve. All the warping functions are constructed based on landmarks that are identified directly from the individual curves. However, there are two main issues with the landmark identification procedure proposed by Gasser and Kneip (1995). Firstly, as the procedure relies on kernel density estimators, accuracy of the kernel density function will always be sensitive to the selected bandwidth. Secondly, the identified landmarks may not have any physical, physiological or kinematic meaning as they are essentially only curve features. In addition, landmark registration cannot be performed if the required set of landmarks is not present on all curves. Lastly, accurate landmark identification can be particularly challenging when ambiguity of landmarks occur such as existence of multiple peaks that are located in close proximity.

In concluding this section of literature review, the following main points should be noted:

- 1) Time normalization is a crucial step that directly affects the accuracy of a kinematic ensemble mean curve.
- 2) Linear time normalization technique is inadequate in normalizing non-periodic and non-cyclical UE movement kinematic data.

- 3) Landmark registration is widely recognized as the best curve registration technique that is useful in performing nonlinear time normalization. Central to landmark registration is landmark identification which continues to be a challenging task.

2.5 Review on kinematics of reach-to-grasp task

Helwig et al. (2011) recommend that in order for data to be analysed holistically, selected landmarks should be kinematically relevant to the task under investigation. Hence, the remaining of this review shall focus on the kinematics of reach-to-grasp so as to identify kinematically relevant landmarks that can be used to perform time normalization on the hand transport TVel curves in this study via a landmark registration procedure. Detail of a new procedure, based on landmark registration, used in this study is found in Chapter 4 of this thesis.

In a reach-to-grasp task, the three main movement components are transport, orientation and grasp (Gosselin-Kessiby et al., 2008). Since the hand transport TVel curves are the primary interest of this study, it shall first be investigated if there are any viable kinematically meaningful landmarks that can be extracted from the TVel curves. There are three obvious events that occur consistently in all TVel curves, namely, (i) movement onset, (ii) maximum TVel amplitude and (iii) movement offset. The hand transport component is in many ways similar to a reaching task. For a reaching task, McCrea et al. (2002) and Murphy et al. (2010) note that the time of occurrence of the peak velocity within the velocity profile is an indicator of strategy. This kinematic parameter also indicates a change from an acceleration phase to a deceleration phase during a reach-to-grasp task. Hence, the times of (i) movement onset, (ii) TVel max and (iii) movement offset will constitute the basic set of landmarks to be used in our landmark registration procedure.

Next, interactions between the transport, orientation and grasp components will be reviewed to determine if the orientation (forearm supination) and grasp components in our reach-to-grasp task affect the hand transport TVel curves in any way. The main purpose is to determine if further effort should be directed towards identifying viable orientation and grasp kinematic parameters that affect the transport TVel, which can then be used as additional landmarks to improve the landmark registration procedure. Though it is debatable how the CNS coordinates these three components to accomplish a reach-to-grasp task, there is no lack of studies demonstrating that difference and perturbation in (i) object size (Castiello et al.,

1993; Paulignan et al., 1991b), (ii) object location (Chieffi et al., 1993; Paulignan et al., 1991a), (iii) object shape (Ansuini et al., 2007; Schettino et al., 2003), (iv) hand aperture size (Saling et al., 1996; Timmann et al., 1996a) or (v) hand orientation on contact (Desmurget et al., 1996; Fan et al., 2006; Herbort & Butz, 2010; Rand & Stelmach, 2005) affects more than one of these three components simultaneously. In such studies, ‘perturbation’ is commonly used to describe a sudden change in parameter(s) shortly after movement onset.

Numerous studies on the effects of changes in grasp on hand transport component have been inspired by Jeannerod’s (1984) important observation that these two components are tightly temporally coupled. In particular, the maximum grip aperture is found to be highly correlated with maximum transport velocity. Grasp changes can be induced by a perturbation in object size or shape at movement onset or simply by altering the starting grasp configuration. Timmann et al. (1996a) and Saling et al. (1996) investigate the effects of altering the starting grasp from a ‘fingers closed’ to ‘fingers apart and fully extended’ (altered condition) configuration. Both studies observed that, in the altered condition, the hand would start to close at movement onset and then reopened before closing onto the object. Using transport time, peak velocity, time to peak velocity, peak acceleration, time to peak acceleration, peak deceleration, time to peak deceleration and deceleration time as the transport kinematic landmarks, Saling et al. (1996) reported a significant increase only in peak acceleration. However, it is found that the grasp and transport components become tightly coupled during the last part of reaching the object. Furthermore, Timmann et al. (1996a) notice that in about 60% of the altered condition transport velocity profiles, there is an inflection that is found to be highly correlated with the reopening of the fingers. In another study by Timmann et al. (1996b), subjects are instructed to perform an additional grasping action to close the hand, during hand transport, before reopening again to grasp an object. This change in grasp kinematic induced the formation of a second hand transport velocity maximum. Despite these changes in the early part of the movement, once again, it is found that grasp and hand transport became tightly coupled as the object approached. All these results are interpreted to support the existence of temporal coupling, and possibly higher order integration, between grasp and transport particularly as the grasp becomes imminent (Saling et al., 1996; Timmann et al., 1996a; Timmann et al., 1996b).

Paulignan et al. (1991b) investigate the effects of reaching to grasp two dowels of different diameter (1.5 cm and 6 cm). It is found that in the unperturbed condition, the time to

maximum grip aperture is found to be longer for the larger cylinder. However, time to peak wrist velocity, amplitude of peak wrist velocity and time to peak wrist deceleration are not significantly different for both sizes. This result is similar to that of Chieffi and Gentilucci (1993) who use six cylinders with diameters ranging from 1 cm to 6 cm. Similarly, time to maximal finger aperture increased significantly with cylinder size. In addition, peak velocity of finger aperture also increased significantly with cylinder size. In contrast, a concurrent significant increase of transport time is observed.

In the size perturbation conditions, Paulignan et al. (1991b) observe an increase in movement time and suggested that this is likely due to lengthening of low velocity portion (deceleration phase). Small changes noted in this low velocity portion are indicative of secondary submovements. For the small to large perturbation condition, the grip aperture exhibited a double peak pattern similar to that reported by Saling et al. (1996) and Timmann et al. (1996b). For the large to small perturbation condition, the enclosure phase is prolonged until the size of the small dowel is reached. Similarly, Dubrowski et al. (2002), using a mixed reality experimental setup, also report increase in transport movement time with both types of size perturbations. Castiello et al. (1993) use two cylinder sizes, 0.7 and 8 cm diameter, to induce precision and whole hand grip respectively. It is noted that during perturbation from large to small cylinder, time of peak wrist deceleration is brought forward without prolonging movement duration in all subjects. For the small to large perturbation condition, only subjects who used a single grip (opening aperture to large object directly without an intermediate closing phase) exhibited the same phenomenon. The peak aperture is attained earlier under both perturbation conditions.

Santello (2002) investigates the evolution of hand shape in grasping objects with different shapes ranging from concave to convex. The angles at the metacarpal-phalangeal (MCP) and proximal interphalangeal (PIP) joints of all four fingers as well as the degree of abduction between the fingers are measured. The MCP, interphalangeal (IP), degree of abduction and rotation angle are measured for the thumb. It is noted that hand shaping occurred in a sequential fashion during reach. Notably, final hand posture is not fully specified at the time of maximum hand opening, rather, different hand postures are maximally discriminated only at contact with object.

Schettino et al. (2003) investigate the effects of convex, concave and regular (rectangular) shaped objects on the hand configuration during grasping. For the convex object, fingers are abducted and the hand is cupped, whereas, for the concave and regular objects, the fingers are adducted. Fingers abduction while grasping convex object is specified very early during movement, implying that hand preshaping started early during movement. Meanwhile, movement time for the concave object is observed to be longest and this is likely due to longer deceleration time. Ansuini et al. (2007) conduct a similar experiment and also noted that reach duration is longer for grasping concave than convex object. Expectedly, the fingers are more flexed, in general, for the concave object. Perturbations from concave to convex object and vice versa resulted in elongation of reach duration. Angular profile analysis of MCP and PIP joints revealed that there is no evident of significant difference near the beginning and end of movement due to perturbation. Considering both perturbation conditions together, all differences in flexion/extension of the MCP and PIP joints are noted between 30% and 80% of the movement duration. So far, evidences supporting that changes in grasp kinematics induced by changes in intrinsic object properties such as size and shape are correlated with corresponding changes in transport kinematics have been discussed.

Next, the effect of changes in object extrinsic properties such as location on the transport and grasp kinematics shall be reviewed. Paulignan et al. (1991a) varied the location of a dowel by positioning it at 10°, 20° and 30° from subjects' midline. Under unperturbed condition, no significant differences are found in both transport and grasp kinematics. On the other hand, Chieffi and Genilucci (1993) place wooden cylinders 7 cm and 17.5 cm from the tips of the thumb and index fingers and note that transport time and time to peak transport velocity increase significantly with distance. Though maximal grip and time to maximal finger aperture are recorded to increase significantly, these do not occur consistently across the different sizes of wooden cylinders (stimuli) used. Thus, the authors caution against the inference that grasp is dependent on object location.

In contrast, when perturbation is introduced such that the object location is changed upon movement onset, movement duration increased significantly and a second velocity peak appeared on the transport velocity profile, indicating use of corrective submovement to reach the correct location (Paulignan et al., 1991a). Interestingly, a similar change in grasp aperture also appeared in 80% of their subjects. Dubrowski et al. (2002) also note that a perturbation in object location influences both the transport and grasp kinematics.

Zaal et al. (1998) find that the hand closure time increases linearly with distance. This occurred for both (i) stationary objects placed at six distances (20 cm to 45 cm) and (ii) objects moving away at three constant speeds (25 cm/s, 35 cm/s and 45 cm/s). The authors further define a variable known as first-order time-to-contact (TC) by dividing the remaining distance between hand and object at the moment of onset of hand closure by the hand velocity relative to the object at the same instance. On the basis that linear relationships existed between TC and stationary object distance and between TC and object moving speed, it is proposed that a continuous dynamical perception-movement coupling exist between transport and grasp. In other words, hand transport provided on-line information for the determination of hand closure initiation. This implies that some aspects of grasp kinematics do depend on object location.

Finally, how object orientation, another extrinsic object property, affects reach-to-grasp kinematics shall now be reviewed. Desmurget et al. (1996) investigate the effects of different object orientations on the transport kinematics under controlled (unperturbed) and perturbed conditions. Briefly, the procedure requires subjects to reach forward vertically, in sagittal plane, to grasp a handle that is oriented at 60°, 40°, 20° and 0° anticlockwise and 20° clockwise relative to the vertical line. In particular, it is reported that wrist path, acceleration time, and acceleration/deceleration ratio are significantly different according to target orientation. The authors conclude that arm transport and hand orientation are implemented and controlled interdependently within an integrated program that seems to involve online updating of upper-limb posture.

Rand and Stelmach (2005) compare the effects of horizontal reach-to-grasp with and without forearm pronation. Pronation is induced by appropriate orientation of the target object. The key finding of this study is that forearm orientation affected both transport and grasping components. With preplanned pronation (without perturbation), transport duration, deceleration time and transport distance increased while peak aperture and aperture closure velocity decreased. Under perturbation condition when the final target orientation required more pronation than the initial target orientation, transport duration and deceleration time increased while the grip aperture profile (time series of grip aperture) changed from a single peak curve to a double peak curve.

Gosselin-Kessiby et al. (2008) require subjects to match targets that are oriented at 60°, 30° and 0° anticlockwise and 30°, 60° and 90° clockwise relative to vertical line. It should be noted that no grasping action is involved as the subjects are holding on to an instrument in their hand with their forearm fully supinated. The task is to reach forward and fit the instrument into a slot in the correct orientation. Under this purely reach-and-orient task, the authors note that as the required degree of rotation (forearm pronation) increased, the peak wrist rotation velocity and peak transport velocity increased concurrently. In a second task, subjects are required to first orient the instrument correctly before reaching forward to the target slot. It is found that the final orientation error at the target is smaller than the initial orientation despite the subjects being instructed not to make any conscious adjustment during the transport of the instrument. This result is interpreted as evidence for the existence of an on-line correction mechanism for hand orientation during reaching to a stationary target.

By requiring subjects to reach towards two turning knobs at two different locations and then turning the knob to a pre-specified angle (either clockwise or anticlockwise), Herbort and Butz (2010) note that the amount of forearm supination is dependent on both the intended direction of turning and location of the knob. This is interpreted to indicate a strong interdependence between the transport and orientation components in a reach-to-grasp task. Finally, although forearm rotation accounted for only 50% of the necessary rotation (the remaining is believed to be accounted for by hand and fingers adjustment), the authors noted that forearm rotation is a good predictor for the final grasp orientation.

In concluding this section of literature review, the following main points should be noted:

- 1) Three basic kinematic landmarks that are suitable to be used as landmarks in the landmark registration procedure to normalize the time of transport TVel curves have been identified. They are times of (i) movement onset, (ii) maximum TVel and (iii) movement offset.
- 2) It should be noted that although the exact nature of interactions between the transport, orientation (mainly forearm supination in this study) and grasp components in various reach-to-grasp tasks appears to be task-specific, it can be concluded that these three components are strongly interdependently controlled by the CNS in a reach-to-grasp task. Hence, a big part of this study shall focus on identifying viable kinematic parameters of the orientation and grasp components that affect the transport TVel to be used as additional landmarks to improve the landmark registration procedure.

Chapter 3

Methods

From the review in Chapter 2, some key points shall be summarised here for easy referencing:

- 1) Reach-to-grasp is a common clinical therapeutic and assessment task.
- 2) Evidences from neuroscience and neurophysiological studies support empirical behavioural observations that reaching is planned and executed in hand space. Thus, tangential velocity (TVel) of hand transport is believed to be the parameter that will best represent a reach-to-grasp task. Furthermore, hand transport TVel is sensitive to pathological reach-to-grasp movements and is easily measurable clinically and thus increases the chance for the results of this study to reach clinical implementation eventually.
- 3) Landmark registration, which is widely accepted to be the best curve registration technique, will be used in time normalization of hand transport TVel curve so as to improve accuracy of the resulting hand transport ensemble mean TVel (EM_TVel) curve representing an individual or group.
- 4) Accurate and meaningful landmark identification is crucial to the success of landmark registration technique. Three basic kinematic landmarks namely time of (i) movement onset, (ii) maximum TVel and (iii) movement offset have been identified.
- 5) The three main movement components of a reach-to-grasp task namely, (i) transport, (ii) orientation (forearm supination) and (iii) grasp are highly interdependent and functionally coupled to achieve a well-coordinated reach-to-grasp action. In particular, changes in orientation and grasping are shown to affect the hand transport TVel.
- 6) In the context of landmark registration of curves, it is hypothesized that forearm supination and grasping will contribute meaningful and important features that can be used as landmarks to improve the time normalization of a set of hand transport TVel curves which in turn will result in a better representative normative hand transport EM_TVel profile.

Therefore, the experiment to be described here in this chapter is aimed at fulfilling the following objectives:

- 1) Determine the set of important forearm supination and grasping kinematic events that affect the hand transport TVel. These identified parameters will then be assessed to determine if they are suitable to be used as additional landmarks to supplement the three identified basic landmarks (Chapter 5).
- 2) Construct hand transport EM_TVel curve for individual subjects from the time normalized hand transport TVel curves and then construct normative representative hand transport EM_TVel curve(s) for all the subjects either as a single group or multiple groups (Chapter 6).

3.1 Subject and preparation

A total of 16 male subjects with mean age 48.7 ± 18.3 years old participated in this study. All subjects are healthy at the time of experiment and have no history of injury to the UE. Fourteen subjects are right-handed. Eleven infrared sensitive reflective markers and 2 marker clusters are used to define upper extremity (UE) model for motion capture at 100Hz using an 8-camera infrared motion capture system (Oqus 1, Qualisys, Sweden). Referring to Figure 3.1, the 11 markers are located at the (1) nail of thumb, (2) nail of index finger, (3) nail of middle finger, (4) head of second metacarpal, (5) head of third metacarpal, (6) capitate bone, (7) radius styloid process, (8) ulnar styloid process, (9) medial epicondyle, (10) lateral epicondyle and (11) acromium. The two marker clusters are located on the forearm and upper arm to improve tracking and post processing interpolation of missing markers especially the ulnar styloid process and medial epicondyle markers.

Figure 3.1: Markers used in defining upper extremity model for motion capture and analysis. 1: nail of thumb, 2: nail of index finger, 3: nail of middle finger, 4: head of second metacarpal, 5: head of third metacarpal, 6: capitate bone, 7: radius styloid process, 8: ulnar styloid process, 9: medial epicondyle, 10: lateral epicondyle, 11: acromium, 12: upper arm cluster and 13: forearm cluster. Two marker clusters are used to improve tracking and interpolation of missing marker via rigid body definition during post processing. Note that the medial epicondyle marker cannot be seen from this angle. It is located on the other side of the elbow closer to the trunk.

3.2 Experiment

Subjects are seated in front of a table such that both their hands are resting on a start position with a forearm flexion of approximately 90° (Figure 3.2). In addition, they are required to rest against the backrest of a chair at all times during the experiment.

There are a total of 4 tasks namely, (i) reach-to-touch (TOU), (ii) reach-supinate-to-touch cylindrical object (SUP), (iii) reach-supinate-to-grasp cylindrical object (CYL) and (iv) reach-supinate-to-grasp cube (CUBE). Subjects are required to perform these tasks in a strict sequential order: $\text{TOU} \rightarrow \text{SUP} \rightarrow \text{CYL} \rightarrow \text{CUBE}$. These tasks are designed such that the entire reach-supinate-to-grasp task is ‘built up’ from scratch. Subjects first start with TOU which only involved horizontal reach and touch. Then the orientation (forearm supination) component is induced and subjects performed reaching and orienting simultaneously in SUP. Finally, the grasp component is added in the CYL and CUBE tasks in which subjects needed to reach, orient and grasp an object. Hence, it is hypothesized that by means of sequential pairwise comparisons of hand transport TVel curves from different tasks, the effect of forearm supination and grasping on the hand transport TVel curve can be elucidated.

Figure 3.2: Plan view of experiment set up. Subject is seated in front of a table. The block arrows illustrate the direction of hand path. First phase is defined as horizontal reaching medially to the first target. Second phase is horizontal reaching away from the body, perpendicular to the frontal plane, to the second target. Returning the hand to starting position consists the third phase.

With reference to Figure 3.2, the procedure for TOU is as follow:

- i) Start with closed hand (thumb in contact with side of index finger) in pronated position.
- ii) Phase 1: reach horizontally and medially to touch a (10×10) cm square target drawn on the table 30 cm away from the start position.
- iii) Phase 2: without pausing, move on to touch another similar target located perpendicularly 30 cm away from the first target.
- iv) Phase 3: again, without pausing, return to starting area with hand pronated but not required to close.

Figure 3.3: Demonstration of the SUP procedure. (a) Starting position. Both hands on table with elbow approximately 90°. Note the left hand is ‘closed’ as if holding a mouse on the table. (b) Left hand moves and touch cylinder. Note that a natural forearm supination is induced by requiring the subject to reach and touch the side of the cylinder. (c) The left hand moving on to touch a second target (square) on the table. (d) The left hand returns to the starting area. Note that the end position of the hand is not required to be closed. The non-participating hand (right in this case) is to remain on the table at all times.

The procedure for SUP (Figure 3.3) is exactly the same as TOU except that the first target is replaced by a cylindrical object (7.5 cm diameter, 9 cm tall and weighs 343 g). Hence, subjects are required to perform forearm supination in order to touch the side of the object with the palm side of the hand. This condition is designed specifically to induce a natural supination action so that comparison with TOU will reveal effect on hand transport TVel by this additional movement component.

Figure 3.4: Demonstration of the CYL procedure. (a) Starting position. Both hands on table with elbow approximately 90°. Note the left hand is ‘closed’ as if holding a mouse on the table. (b) Left hand moves and grasps the cylinder. (c) The cylinder is transported to a target located 30 cm away perpendicularly. Accuracy of cylinder placement in the target area is not important. (d) The left hand returns to the starting area. Note that the end position of the hand is not required to be closed. The non-participating hand (right in this case) is to remain on the table at all times.

The procedure for CYL (Figure 3.4) is exactly the same as SUP except subjects are required to grasp the cylindrical object and transport it to a second target located 30 cm perpendicularly from the first target (Figure 3.2). This condition is designed specifically to induce a natural grasping action so that comparison with SUP will reveal effect on hand transport TVel with this additional movement component. In this study, hand aperture is defined to be the distance between thumb and middle finger. The middle finger is chosen

instead of the index finger when it is observed during post processing that all subjects grasp with their thumb and middle finger. The index finger is sometimes used for fine adjustment even during transportation of the object.

The procedure for CUBE is exactly the same as CYL except that the object is replaced by a 7.5 cm wooden cube weighing 343 g. Note that the size and weight of this cube is similar to the cylinder used in CYL. It is thus expected that the grip size will remain constant. This condition is designed to investigate if the hand transport TVel will be affected by a change of object shape that effectively reduces the number of opposition axis from infinity to 2. An opposition axis is defined to be the axis along which the thumb and the finger(s) grasp the object.

Subjects are instructed to perform all the above tasks in their natural speed and that accuracy is not important. It is emphasized that the tasks should be completed as smoothly as possible without stopping at the targets. Before commencement with data collection of a task, an experimenter would demonstrate the performance of the task. Then, subjects are allowed ample time to practise the tasks until they feel that they are comfortably familiar with the task.

Each subject is required to perform 10 trials for each of the above 4 tasks in the order that they are described here. The 10 trials are completed in two sets of 5 trials. Each trial begins and ends at the command of the experimenter. Subjects are instructed to close their hand upon hearing the 'stop' command at the end of a trial. A short interval of 1 min rest is given between each set of trial. Two trials are discarded due to experimental error resulting in a total of 638 trials used in the final analysis.

The number of trials (10 trials) per trial per subject is selected based on literature review on previous studies on upper extremity movements and reach-to-grasp tasks. In an attempt to establish normative angular characteristics of four ADL tasks, van Andel et al (2008) use 3 trials per task per subject. Butler et al (2010) also use 3 trials per task per subject to establish normative angular kinematics of reach-to-grasp task in subjects aged between 5 and 18 years old. Coluccini et al (2007) establish normative kinematic characteristic of 11 year old subjects using only 3 trials per subject. Murgia et al (2010) use 4 trials to establish normative angular kinematics of a page turning task on subjects with average age 32.5 yrs, SD 10.7 yrs. Coderre et al (2010) perform assessment of upper limb sensorimotor function of sub-acute

stroke patients using visually guided reaching and established control (based on normal control subjects) kinematic values using only 8 trials per subject. Ronnqvist & Rosblad (2007) also perform 8 trials on each of the 11 control children to establish control (normative) kinematics of reaching and grasping movement for the purpose of comparison with children suffering from cerebral palsy.

In addition, sequential averaging analysis (James, 2004; James, et al., 2007) is performed to determine if the reach-to-grasp movement pattern has stabilised within 10 trials for all the subjects. Movement pattern is characterised by the following kinematic parameters: (i) max TVel, (ii) mean TVel, (iii) max TAcc, (iv) min TAcc, (v) MedianLC (spatial smoothness), (vi) normalised Jerk score (temporal smoothness), (vii) approach TVel and (viii) max TVel relative timing. In this study, 10 trials (except for 2 subjects who only have 9 valid trials due to experimental errors) are used to calculate the reference mean values for each of the above list of parameters. Starting from the first trial, subsequent trials are sequentially included one at a time at each iteration and a cumulative mean is calculated for each iteration. In this way, the cumulative mean of all 10 trials is the same as the reference mean (James, et al., 2007). At each iteration, the absolute difference between the cumulative mean and the reference mean is calculated. Stability of a parameter is achieved with a certain number of trials when all successive absolute differences are below a predefined criterion value (James, et al., 2007). In this study, the criterion value is set at 0.3 standard deviation of all the 10 trials. For each of the 8 parameters, the minimum number of trials required to achieve stability is recorded. Finally, the maximum of these minimum values is recorded for each subject per task and presented in Table 3.1. From the result in Table 3.1, it can be concluded that all subjects achieve movement stability, relative to the 8 selected kinematic parameters within 10 trials. James, et al. (2007) note that this method of estimating the number of trials necessary to achieve movement stability is conservative as compared to intra-class correlation coefficient analysis method. Moreover, all subjects are given ample practices prior to the commencement of actual data collection. This implies that all subjects effectively perform each task more than 10 times. Thus, it is possible that the 10 recorded trials are sufficient to provide the required movement stability for this study.

Table 3.1: Minimum number of trials per task per subject. Sequential averaging analysis (James, et al., 2007) was performed to determine the stability of max TVel, mean TVel, max TAcc, min TAcc, MedianLC, normalised Jerk score, approach TVel and max TVel relative timing based on 10 trials (except Sub11-SUP and Sub16-CYL who only have 9 trials due to experimental error) and 0.3 standard deviation criterion.

Sub	TOU	SUP	CYL	CUBE
1	9	7	9	9
2	8	9	5	6
3	8	8	7	8
4	9	9	8	6
5	9	9	9	8
6	8	7	7	9
7	9	9	9	8
8	8	7	9	8
9	8	7	8	8
10	8	9	8	9
11	8	7	8	9
12	8	8	7	8
13	8	7	9	9
14	9	9	9	8
15	7	9	9	9
16	9	8	8	7

3.3 Data processing

In this project, only Phase 1 of the entire movement is considered. That is, analysis shall only focus on horizontal reaching towards the first target.

The radius styloid process marker, ulnar styloid process marker and forearm marker cluster (Figure 3.1) define the forearm rigid body (Figure 3.5b). The medial epicondyle marker, lateral epicondyle marker, acromium marker and upper arm marker cluster (Figure 3.1) define the upper arm rigid body (Figure 3.5b). Missing marker data is interpolated using the Qualisys Track Manager (QTM) software's rigid body capability (Soderkvist & Wedin, 1993). To facilitate this, at the beginning of each set of trials, subjects are required to raise their hands above their head for approximately 3 seconds. This would ensure that all markers, especially the medial epicondyle marker, could be captured by the cameras. Markers in these frames are then used to define the rigid bodies as described above. For any given frame, a rigid body required a minimum of 3 markers to be visible. Once the rigid bodies are defined, the markers on each rigid body are expected to maintain constant relative distances from one another within a user specified error tolerance level. Due to limitation in QTM, tolerance

level could only be set at the global level, that is, all rigid bodies shared the same level of error tolerance. In this study, the maximum level of error tolerance is set at 30 mm. Hence if the relative distances of a marker to all other markers on the same rigid body exceeded 30 mm for certain frames, that rigid body would not be defined for those frames. In such cases, frame-by-frame inspection of 3D trajectories is performed to identify and remove the erroneous marker visually for the affected frames. Once the erroneous marker is removed, QTM would use the remaining (at least 3) markers to define the rigid body for the affected frames. In the process of doing so, the removed marker would be treated as missing marker and its trajectory would be interpolated by the remaining markers on the same rigid body. This is illustrated with an example of the missing medial epicondyle marker which is part of the upper arm rigid body (Figure 3.5b). The elbow width is calculated as the distance between the medial epicondyle and lateral epicondyle markers (elbow markers). In Figure 3.6a, the elbow width of a typical subject is shown for an entire duration of a trial. The big gap observed on the graph is the result of missing medial epicondyle marker due to occlusion during motion capture. Occlusion and low tracking accuracy are particularly common for this marker as it is located between the elbow and the trunk and faces downwards towards the ground during the reach-to-grasp tasks in this study. In Figure 3.6b, the gap is filled in by using applying single marker interpolation on the medial epicondyle marker. However, note that the elbow width ranges approximately from 78.0 to 93.2 mm. This undesirably large range is the result of low tracking accuracy of the medial epicondyle marker during movement. As the tracking accuracy of medial epicondyle marker is low during movement, its entire trajectory is removed and then recalculated using the upper arm rigid body as described above. The result in Figure 3.6c shows that the elbow width calculated based on this rigid body derived medial epicondyle trajectory is much more accurate ranging approximately from 80.6 to 82.6 mm.

(a)

(b)

Figure 3.5 Upper extremity markers captured in QTM software. (a) Illustrates the individual markers captured in QTM without rigid body defined. 1: nail of thumb, 2: nail of index finger, 3: nail of middle finger, 4: head of second metacarpal, 5: head of third metacarpal, 6: capitate bone, 7: radius styloid process, 8: ulnar styloid process, 9: medial epicondyle, 10: lateral epicondyle, 11: acromium, 12: upper arm cluster and 13: forearm cluster. (b) Upper arm rigid body (magenta) is defined by medial epicondyle, lateral epicondyle and upper arm cluster. Forearm rigid body (blue) is defined by radius styloid process, ulnar styloid process and forearm cluster.

(a)

(b)

(c)

Figure 3.6: Elbow width is calculated as distance between (9) medial epicondyle and (10) lateral epicondyle markers. (a) This is the elbow width calculated from marker positions without rigid body (as in Figure 3.5a). Note that the big gap is due to the missing (9) medial epicondyle marker as a result of occlusion. (b) Shows the interpolated result using single marker interpolation. Note also that in (a) and (b) the elbow width changes drastically due to inaccuracy in tracking (9) medial epicondyle marker. (c) Estimation and interpolation of (9) medial epicondyle marker using upper arm rigid body (Figure 3.5b) leads to much more stable elbow width measurement. This implies that (9) medial epicondyle marker data is more accurate in this case.

After missing marker data interpolation, all 3D position data is exported to Matlab. A second order zero-lag Butterworth 6Hz low pass filter is applied (Wagner et al, 2006; Coluccini et al, 2007; Wagner et al, 2008; Murgia et al, 2010; Murphy et al, 2010). Then, hand TVel is calculated from the filtered capitate marker's 3D position data (Roby-Brami et al, 2003; Supuk et al, 2011) using the forward difference method. Movement onset is defined to be 2% of the maximum hand transport TVel in the first phase (Figure 3.7). The first minimum point in hand transport TVel after contacting the first target or grasping the object is taken to be a transition to the second phase and is thus used to mark movement offset of the first phase (Figure 3.7). Target or object contact time is determined by frame-by-frame visual inspection of 3D trajectories and corresponding video recordings. Target or object contact time is defined as follow for the four tasks:

- (i) TOU and SUP: the time when tip of either the index or middle finger first touches the target.
- (ii) CYL and CUBE: the time when both the thumb and middle finger first touch the object.

Figure 3.7: Phase 1 movement onset offset detection. The figure shows a typical hand tangential velocity (TVel) profile of the task in this study. Phase 1 is the reach-supinate-to-grasp phase and is the focus of this study. Onset time is defined to be the time when 2% of the TVel maximum of Phase 1 is attained. Offset time is defined to be the time of first minimum after TVel maximum of Phase 1.

After all the Phase 1 hand transport TVel curves of all the 4 tasks have been extracted, each subject will have a maximum of 40 hand transport TVel curves with 9 to 10 curves per task (Figure 3.8). Recall that the main purpose of performing the 4 tasks is to compare and contrast the hand transport TVel curves from each task so as to understand how these curves change in the presence of forearm supination and grasping. In order to do so, for each subject, it is necessary to construct a representative hand transport EM_TV_{el} curve from the hand transport TV_{el} curves for each task so that the comparisons can be performed via these hand transport EM_TV_{el} curves.

Figure 3.8: Hand transport TV_{el} curves of a typical subject for Phase 1 Iteration 0. Iteration 0 refers to the original state without time normalisation. TV_{el} curves of (a) TOU, (b) SUP, (c) CYL and (d) CUBE task. Note that all these curves are not time normalised, hence, EM_TV_{el} curves calculated from these 4 sets of TV_{el} curves are inaccurate. Furthermore, direct curve comparisons are limited with different domains.

As can be observed in Figure 3.8 as well as noted in Section 2.4, time normalisation of these hand transport TV_{el} curves is a necessary and crucial step that directly determines the

accuracy the resulting hand transport EM_TVel curves. The review in Section 2.4 clearly stated the limitations of linear time normalisation based only on movement onset and offset times and that it is important to align kinematically significant events. Hence, as stated in Section 2.5 as well as the beginning of this chapter (points 3 and 4) that times of (i) movement onset, (ii) maximum TVel and (iii) movement offset will be used as the three basic landmarks to perform nonlinear landmark registration to normalise the time domain of each set of hand transport TVel curves as shown in Figure 3.8.

It is important that a time normalisation procedure preserves the corresponding temporal relationships between the hand transport, forearm supination and grasping kinematics. In this way, any observed differences within a time interval between the hand transport EM_TVel curves of two experimental tasks can be checked for possible association with significant forearm supination and/or grasping kinematic events over the same time interval. In fact, this is the scope to be covered in Chapter 5. Hence, in Chapter 4, a novel landmark registration technique will be proposed so as to perform nonlinear time normalisation in such a way as to facilitate the work to be accomplished in Chapters 5 and 6.

Chapter 4

Nonlinear Landmark Registration for Time Normalisation

Ultimately, this project aims to construct representative normative EM_TV_{el} curve for the hand transport component of a reach-to-grasp task against which pathological movements can be compared and assessed. To accomplish this, proper time normalisation of the individual hand transport TV_{el} curves is crucial as it directly affects the accuracy of the hand transport EM_TV_{el} curve calculated based on these curves.

Landmark registration has been identified to be the best curve registration technique (Section 2.4) to be used in this project to perform time normalisation of the individual hand transport TV_{el} curves obtained in the experiment described in Chapter 3. A set of 3 basic kinematic landmarks have been identified based on characteristics of the hand transport TV_{el} curves (Section 2.5). However, these do not account for the effects that forearm supination and/or grasping may have on the hand transport TV_{el} curve. In other words, it is yet to be determined if there exist any forearm supination and/or grasping kinematic events that significantly affect the hand transport TV_{el} (Chapter 5). For example, since the SUP and CYL tasks (Section 3.2) differ only in that the CYL task involved the grasping component, it is possible for a significant difference between the hand transport EM_TV_{el} curves of these tasks to be associated with a grasping kinematic event, if these occur within a same time interval .

In order to facilitate such comparisons and associations, if they exist, it is necessary to preserve the temporal correspondence between kinematic events of the hand transport, forearm supination and grasping components after time normalisation. One possible solution is to perform time normalisation in the position domain. That is, time normalisation is performed on the x , y and z position data simultaneously. Since all hand transport, forearm supination and grasping kinematic parameters are derived from a common 3D position data source, this process of time normalisation in the position domain will preserve the temporal correspondence between kinematic events of the three movement components. For example, if the time of occurrence of maximum hand transport TV_{el} corresponds to the time of occurrence of initiation of grasping (hand aperture closure) in the original data, this temporal correspondence between these two kinematic events will be preserved.

However, time normalisation of 3D position domain alone is unlikely to result in properly aligned hand transport TVel curves. Hence, the objective of this chapter is to propose a novel landmark based registration procedure that will achieve proper time normalisation of hand transport TVel curves while preserving the temporal correspondence between kinematic events of the hand transport, forearm supination and grasping components. The procedure is described and illustrated in Section 4.1. Rationale underlying some important and novel steps of the proposed procedure will be discussed in Section 4.2. Then, the procedure is applied to the experimental data from Chapter 3 in Section 4.3 and will also be compared with the linear time normalisation (LTN) procedure. Finally, this chapter ends with some concluding remarks in Section 4.4.

4.1 Procedure

Step 1: Landmarks identification

As is noted in Section 2.5, times of (i) movement onset, (ii) maximum TVel and (iii) movement offset are the 3 identified basic temporal landmarks as illustrated in Figure 4.1.

Here, tangential velocity is defined as

$$V = \sqrt{V_x^2 + V_y^2 + V_z^2} \quad (4.1)$$

where V_x , V_y and V_z are the velocities in the three principal directions, calculated from the forward difference of x , y and z position components.

Step 2: Calculation of target locations for landmarks

Assuming there are N curves (trials) with M number of selected landmarks per curve, the set containing time of occurrences of these landmarks is $\{t_{1,1}, t_{1,2}, \dots, t_{1,M}, t_{2,1}, t_{2,2}, \dots, t_{2,M}, \dots, t_{N,M}\}$ where $t_{i,j}$ is the time of occurrence of the j^{th} ($j = 1, \dots, M$) landmark for the i^{th} ($i = 1, \dots, N$) curve. Define

$$T_j = \frac{\sum_{i=1}^N t_{i,j}}{N} \quad (4.2)$$

where T_j is the mean time location of the j^{th} landmark and is also the target location for all the N number of j^{th} landmarks (Figure 4.1). That is,

$$w_i: t_{i,j} \rightarrow T_j \quad (4.3)$$

where w_i is the warping function, to be determined, for the i^{th} curve.

Figure 4.1: Illustration of landmarks identification and target locations calculation. Two typical tangential velocity profiles are used in this illustration. The movement onset time (T_1), time of occurrence of maximum tangential velocity (T_2) and movement offset time (T_3) are calculated as means of these events from the individual profiles.

Time of maximum hand transport TVel is located using the `find` and `max` functions in Matlab to search for the location of maximum hand transport TVel. Movement onset time is defined to be the location of 2% of the maximum hand transport. This is again achieved using the `find` function in Matlab. The first minimum point in hand transport TVel after contacting the target or grasping the object is used to mark movement offset. Target or object contact time is determined by frame-by-frame visual inspection of 3D trajectories and corresponding video recordings.

Step 3: Determining the warping function

Note from the above definition, the warping function for a curve is uniquely and fully defined by landmarks of that curve. The warping function must be a continuous monotone function (Ramsay & Silverman, 2006). Since time is increasing, a monotonically increasing function

is needed. By plotting original time t_{ij} on the abscissa and the corresponding target time T_j on the ordinate for the i^{th} curve, the time warping function, w_i , is constructed by interpolating these points with a piecewise cubic Hermite interpolating polynomial (Figure 4.2). This can be achieved by using the ‘pchip’ function in Matlab.

Figure 4.2: Determination of warping functions for each curve (trial). The abscissa is the original time and the ordinate is the target time. The red and blue dots are time coordinates of the identified landmarks for the red and blue velocity profiles respectively, that is, $\{(0, T_1), (t_{2,1}, T_2), (t_{3,1}, T_3)\}$ and $\{(0, T_1), (t_{2,2}, T_2), (t_{3,2}, T_3)\}$ are the sets of time coordinates used in determining the respective warping functions. Piecewise Hermite cubic interpolating polynomials are used to interpolate these points and obtain the warping functions.

Step 4: Curve registration (time warping)

Apply warping function w_i to time warp the i^{th} curve. In this project, although landmark locations are obtained from hand tangential velocity profile, actual curve registration (time warping) is performed in position space. In other words, warping function, w_i , is applied to warp the x , y and z positional data (Figure 4.3) of the i^{th} curve (trial). Since the same warping function is applied to these three position components, the resultant 3D path of the movement is preserved. Also, the corresponding temporal relationships between any kinematic parameters that are derived from the position data will be preserved. The warped position data for each trial is then used to calculate the corresponding warped tangential velocity for that trial as above (Figure 4.4). This step is unique to this proposed procedure.

Figure 4.3: Illustration of application of red time warping function (Figure 4.2). Nonlinear time normalisation (NTN) is performed using the warping function in the position domain on the x , y and z axes simultaneously. Dashed red curves are the original position curves. Solid red curves are the corresponding time warped curves. Note that the amplitude of the position curves is not altered after warping. Only the time domain has changed. As all three axes are subjected to the same time warping, the resultant 3D path is not affected.

Figure 4.4: The time warped position data is used to calculate the warped tangential velocity profiles. Note that since time is warped in the position domain, the resulting tangential velocity profiles are shifted in time as well as altered in amplitude. Hence, it should be noted that the peak tangential velocities may not be fully aligned in time. Better alignment can be achieved with more iterations.

Step 5: Construct ensemble mean curve and estimate data variance

Based on the N registered (warped) tangential velocity curves, an ensemble mean curve is constructed using the point-by-point averaging method. That is, assuming there are K discrete time points, the ensemble mean (EM) curve and the standard deviation (SD) are given by

$$EM_k = \frac{\sum_{i=1}^N V_{i,k}}{N} \quad (4.4)$$

$$SD_k = \sqrt{\frac{\sum_{i=1}^N (V_{i,k} - EM_k)^2}{N - 1}} \quad (4.5)$$

where $V_{i,k}$ is the tangential velocity of i^{th} curve (trial) at the k^{th} time point and EM_k and SD_k are the mean tangential velocity and standard deviation respectively at the k^{th} time point (Figure 4.5). Next, a set of collection of all the SD_k for each iteration is defined as

$$SD_{ltr} = \{SD_1, SD_2, \dots, SD_k, \dots, SD_K\} \quad (4.6)$$

where ltr is the iteration number.

Figure 4.5: Point-by-point ensemble mean curve (blue dotted curve) and its SD bounds (red dashed curves). SD is calculated at discrete time points. SD_k is the SD calculated at k^{th} time point.

Step 6: Iteration and termination criteria

If $Itr = 1$ (after first iteration), repeat Step 1-5. For $Itr > 1$, a 2-tailed two-sample t -test and a 2-tailed two-sample Wilcoxon rank sum test comparing the mean and median, respectively, between SD_{Itr} and SD_{Itr-1} are performed. The p -values of these two tests are calculated and used as iteration termination criteria. Iteration is terminated only if both p -values are greater than 0.05, otherwise, repeat Step 1-5. Essentially, this is an indication that iteration Itr does not result in significant differences in both the mean and median SD of the tangential velocity data as compared with those in iteration $Itr-1$. Since the rationale behind time warping is to remove the adverse effect of curves misalignment on data variance, iteration will be terminated when further iteration no longer makes any significant difference to the data variance. Finally, iteration $Itr-1$ contains the final warped data.

4.2 Discussion on rationale underlying procedure

This section highlights the rationale underlying the novel procedures in Step 4 and 6. It is important to recall that the above novel landmark based registration procedure is proposed to achieve proper time normalisation of hand transport TVel curves while preserving the temporal relationships between the hand transport, forearm supination and grasping components. The choice of performing time normalisation on the common 3D position domain (Step 4) is a logical one as this will naturally preserve the important corresponding

temporal relationships between the three main movement components. However, this has a side-effect that identified important kinematic landmarks on the transport TVel curves may not be properly aligned in a single iteration as illustrated in Figure 4.4.

Consequently, a stopping criterion is needed to terminate the iterative procedure when the TVel curves are assessed to be ‘properly aligned’. A set of curves can be considered to be ‘properly aligned’ once all the identified kinematic landmarks are aligned resulting in the removal or minimisation of unwanted temporal variations. In the above procedure, it should be noted that because time normalisation is performed on the position data, not directly on the TVel curves, the amplitude of the resulting TVel curves are also altered (Figure 4.4). This effect is investigated mathematically as follow:

Given 3D position data $(x(t), y(t), z(t))$ and a warping function w such that $w(t) = T$, $x(w(t)) = x(T) = x(t)$. That is, the warping function, w , changed the time domain without changing the amplitudes of x , y and z . Now, in this study the TVel is defined as

$$V(t) = \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2 + \left(\frac{dz(t)}{dt}\right)^2} \quad (4.7)$$

The NTN procedure proposed in this chapter involves time warping of the position data, that is, $(x(t), y(t), z(t)) \rightarrow (x(T), y(T), z(T))$. Using this time warped position data, the resulting TVel is thus

$$\begin{aligned} V(T) &= \sqrt{\left(\frac{dx(T)}{dT}\right)^2 + \left(\frac{dy(T)}{dT}\right)^2 + \left(\frac{dz(T)}{dT}\right)^2} \\ &\approx \sqrt{\left(\frac{\Delta x(T)}{\Delta T}\right)^2 + \left(\frac{\Delta y(T)}{\Delta T}\right)^2 + \left(\frac{\Delta z(T)}{\Delta T}\right)^2} \end{aligned} \quad (4.8)$$

Now, for the case when time warping is performed directly on the TVel as defined in Eq (4.7), the resulting tangential velocity is

$$\begin{aligned}
V_{Direct}(T) &\approx \sqrt{\left(\frac{\Delta x(T)}{\Delta t}\right)^2 + \left(\frac{\Delta y(T)}{\Delta t}\right)^2 + \left(\frac{\Delta z(T)}{\Delta t}\right)^2} \\
&= \sqrt{\left(\frac{\Delta T}{\Delta t} \times \frac{\Delta x(T)}{\Delta T}\right)^2 + \left(\frac{\Delta T}{\Delta t} \times \frac{\Delta y(T)}{\Delta T}\right)^2 + \left(\frac{\Delta T}{\Delta t} \times \frac{\Delta z(T)}{\Delta T}\right)^2} \\
&= \sqrt{\left(\frac{\Delta x(T)}{\Delta T}\right)^2 + \left(\frac{\Delta y(T)}{\Delta T}\right)^2 + \left(\frac{\Delta z(T)}{\Delta T}\right)^2} \times \left(\frac{\Delta T}{\Delta t}\right) \\
&= V(T) \times \left(\frac{\Delta T}{\Delta t}\right)
\end{aligned}$$

Hence,

$$V(T) = \left(\frac{\Delta T}{\Delta t}\right)^{-1} V_{Direct}(T) \quad (4.9)$$

where V is the warped TVel obtained via the proposed procedure (Section 4.1), V_{Direct} is the warped TVel when warping is done directly in the TVel domain and $\Delta T/\Delta t$ is the gradient of the warping function. Essentially, Eq 4.9 illustrates that the TVel obtained from the proposed procedure is affected by the gradient of the warping function. In other words, a warping function with gradient significantly different from one can cause significant amount of amplitude distortion in the warped TVel profile. As a result, kinematic landmarks on the time normalised TVel curves may never be aligned exactly. Hence a stopping criterion based solely on the exact alignment of kinematic landmarks is likely to result in infinite iterative loops in this procedure.

The need for curve registration (time normalisation) to be performed on a set of curves is justified when the physical time does not adequately account for an underlying dynamic process of the system under investigation (Ramsay & Silverman, 2006). The underlying assumption is that time normalisation will remove unwanted temporal variations that contaminate the ‘true amplitude variance’. However, a fundamental flaw in this assumption is that the ‘true amplitude variance’ is practically undefined. Hence, defining a ‘variance threshold’ as an iteration termination criterion is likely to be highly subjective. This problem is circumvented by the novel termination criteria described in Step 6. Essentially, the termination criterion in Step 6 seeks to detect a lack of change in data variance in consecutive iterations. Though this cannot guarantee to achieve ‘true amplitude variance’, it can definitely

reduce the likelihood of ‘over-registration’. This is especially important in this procedure as ‘over-registration’ will cause unnecessary changes in TVel amplitude.

4.3 Application of nonlinear landmark registration to time normalise experiment data

In this section, the above procedure (Section 4.1) is implemented to normalise the time domain of the experimental data collected in Chapter 3. A total of 64 sets of data are used (16 subjects $\times$ 4 tasks). Each set of data consists of 9 to 10 trials from a single subject. Raghavan et al., (2010) justified a linear time normalisation procedure by citing the works of Santello and Soechting (1998), Schettino et al. (2003) and Winges et al. (2003) which show that temporal evolution of reach-to-grasp in healthy subjects are independent of reach speed. Guigon, Baraduc and Desmurget (2007) propose that motor control is governed by four principles, (i) *separation* in planning of static and dynamic forces, (ii) *optimal feedback control* of dynamic forces, (iii) *maximum efficiency* in control of movement parameters and (iv) *constant effort* for all movements obeying a given set of instructions. Comparison of this model’s output with experimental results shows that TVel profiles of end-effector for point-to-point movements, especially those that are symmetrical, have an invariant shape and scale in time and magnitude. Furthermore, Ganesh et al., (2010) demonstrate that for a subject, muscle memory and muscle activation history play important roles in the selection of motor strategy for a given task. In that study, subjects are required to learn an optimal co-activation strategy of the wrist flexor and extensor muscles in order to maintain a virtual object (presented via a computer program) within a target area. After learning the optimal strategy, each subject is forced to learn sub-optimal co-activation strategies which remain successful in fulfilling task requirements. It is reported that subjects adopt the most recent activation strategy even if it is not optimal. This shows that for a familiar and well-learnt task in a single session of experiment, it is conceivable that a subject will converge to a single motor strategy to perform the task. Under this assumption, it is thus reasonable to assume that each subject uses a single strategy to perform all the 10 trials which were conducted within a single session of experiment. Therefore, this justifies the use of the non-linear time normalisation of the TVel profiles that aims to minimise temporal variations of key kinematic landmarks as the times of occurrence of these landmarks are believed to be characteristic of a motor strategy.

The results of applying the above procedure are illustrated on the CYL task for one typical subject in Section 4.3.1 (results for this subjects for all 4 tasks are presented in Appendix A).

Finally, results of this nonlinear time normalisation (NTN) procedure are compared with the linear time normalisation (LTN) procedure in Section 4.3.2.

4.3.1 Results of nonlinear time normalisation (NTN) on one typical subject

The results of applying the NTN procedure (Section 4.1) to a typical subject performing the CYL task (Section 3.2) are presented in Figure 4.6 and Table 4.1. The left column of Figure 4.6 shows the changes of the TVel curves at each iteration. Note that the maximum TVels of all the curves are not aligned after the first iteration. Also, observe that the amplitude of some TVel curves changed. Take the red curve (Trial 1) for example, observe that not only has the max TVel position shifted left temporally, it has also increased by about 0.1 mm/msec. This increase is directly proportional to the inverse gradient (Eq 4.9) of the corresponding red warping function (Figure 4.6). As the gradients of the warping functions converge to 1, the corresponding changes in TVel amplitudes decrease. It is important to note that convergence of the gradients of warping functions to 1 is not the stopping criterion. This is because applying such a stopping criterion would be equivalent to requiring exact alignment of kinematic landmarks which has been discussed to be impossible in some cases (Section 4.2). Furthermore, the process of setting an acceptable margin of error around gradient 1 as a termination threshold is likely to be subjective.

Figure 4.6: Nonlinear landmark registration to normalise time for 1 typical subject. Left column: individual trial TVel for each iteration. Right column: warping functions for each iteration. Black arrow indicates the set of curves used to construct the warping functions. White arrow indicates the result of warping the time in position domain. The process terminated in 3 iterations and the 2nd iteration was taken as the final result.

Table 4.1 shows the results of comparing data variance between consecutive iterations. As can be observed, the p -values in columns 3 and 5 increase with each iteration. The iterative procedure is terminated when both of these p -values exceed 0.05 level of significance. These indicate that the data variance, as assessed by 2-sample t -test and 2-sample Wilcoxon rank sum test, is no longer changing significantly in consecutive iterations. Hence, further time warping is deemed unnecessary as this will no longer affect the data variance. From Table 4.1, it can be clearly seen that both p -values exceed 0.05 at iteration 3. This implies that there is not sufficient evidence to conclude that the data variance in iteration 2 is significantly different from the data variance in iteration 3. Consequently, the iterative process is terminated and the TVel curves in iteration 2 are taken to be the final time normalised curves.

Table 4.1: Results of comparing data variance between consecutive iterations. 2-sample t -test is used to test the difference between the means of standard deviation (SD) between consecutive iterations. 2-sample Wilcoxon rank sum test is used to test the difference between the medians of SD between consecutive iterations. Negative values in columns 2 and 4 indicate a decrease in SD as compared to the previous iteration.

Iteration	Difference in mean SD	p -value	Difference in median SD	p -value
1	-0.0522	0.0000	-0.0490	0.0001
2	-0.0073	0.0057	-0.0152	0.0102
3	0.0000	1.0000	0.0000	1.0000

4.3.2 Comparison of NTN and LTN procedures

In this section, the results of applying the NTN and LTN procedures on all 64 sets (638 trials in total) of experimental data (Chapter 3) will be compared. The performance of these procedures will be evaluated based on their effects on the data variance as well as the degree of representativeness of the resulting EM_TV_{el} curve.

4.3.2.1 Effects of NTN and LTN on data variance

For each set of data, point-by-point ensemble mean curves were constructed for the original data ($EM_{ORG,Set}$), linearly normalised data ($EM_{LTN,Set}$) and nonlinearly time normalised data ($EM_{NTN,Set}$). $EM_{ORG,1}$ denotes the ensemble mean curve for set 1 of original non-normalised data. $SD_{ORG,Set}$, $SD_{LTN,Set}$ and $SD_{NTN,Set}$ were also calculated. Here $SD_{ORG,1}$, for example, is a set of collection of all SD_k (as described in Section 4.1 Step 5 above) for set 1 of original non-

normalised data. In addition, the coefficient of variation (CV) (Winter, 1984) was also calculated based on the ensemble mean curve and standard deviation (SD) of data as:

$$CV_{Set} = \frac{\sqrt{\frac{\sum_{k=1}^K (SD_{Set,k})^2}{K}}}{\frac{\sum_{k=1}^K EM_{Set,k}}{K}} \quad (4.10)$$

Hence, the effect of warping on data variance will be investigated using $SD_{ORG,Set}$, $SD_{LTN,Set}$, $SD_{NTN,Set}$, $CV_{ORG,Set}$, $CV_{LTN,Set}$ and $CV_{NTN,Set}$.

For brevity, Table 4.2 contains a truncated version of the 64 sets of comparisons of SD distribution between NTN, ORG and LTN data. To obtain the mean of SD_{NTN} for data set 1 in the table (entry in second row, second column), for example, we need to define

$$SD_{NTN,1} = \{SD_{1,1}, SD_{1,2}, SD_{1,3}, \dots, SD_{1,k}, \dots, SD_{1,K}\} \quad (4.11)$$

that is, a set of collection of SD for all K time points for NTN condition. Thus,

$$\text{mean of } SD_{NTN,1} = \frac{\sum_{k=1}^K SD_{1,k}}{K} \quad (4.12)$$

The p -values in the fourth and sixth columns of Table 4.2 are results of 2-tailed t -tests conducted to test for differences between the means of SD_{NTN} and SD_{ORG} and between the means of SD_{NTN} and SD_{LTN} respectively. Assessed at a significance level of 0.05, Table 4.2 shows that by performing NTN, the resulting mean SD differs significantly for approximately 85.94% and 71.88% of the number of data sets when compared with that obtained from the ORG and LTN methods respectively. In fact, 81.52% and 68.75% of the sets of data exhibited lower mean SD for the NTN procedure as compared with the ORG and LTN procedures respectively.

Table 4.2: Comparison of standard deviation (SD) distribution of nonlinearly time normalised (NTN), original non-normalised (ORG) and linearly time normalised (LTN) data. 2-tailed t -tests were conducted.

Data set	Mean of SD_{NTN} (A)	Mean of SD_{ORG} (B)	t -test (p -value) (A vs B)	Mean of SD_{LTN} (C)	t -test (p -value) (A vs C)
1	0.0206	0.0309	1.2022E-07	0.0317	9.7459E-11
2	0.0173	0.0253	1.4254E-06	0.0283	9.8173E-08
3	0.0198	0.0266	1.4321E-05	0.0217	0.0925
4	0.0210	0.0355	5.3591E-08	0.0273	9.1978E-05
⋮	⋮	⋮	⋮	⋮	⋮
64	0.0388	0.0817	1.0462E-06	0.0563	6.0341E-05
% of sets with p -value < 0.05			85.94% (55/64)		71.88% (46/64)
% of sets with significantly lower (A)			81.25% (52/64)		68.75% (44/64)

Table 4.3: Comparison of coefficient of variation (CV) of nonlinearly time normalised (NTN), original non-normalised (ORG) and linearly time normalised (LTN) data. 2-tailed t -tests were conducted.

Data set	CV_{NTN}	CV_{ORG}	CV_{LTN}
1	0.0592	0.0983	0.0897
2	0.0560	0.0913	0.0968
3	0.0704	0.1032	0.0774
4	0.0705	0.1383	0.0934
⋮	⋮	⋮	⋮
64	0.1188	0.3149	0.1694
Mean	0.1041	0.1897	0.1486
p -value (compare with NTN)		7.1834E-16	3.0814E-10
% of sets with lower CV_{NTN}		95.31% (61/64)	90.63% (58/64)

(a) Original TVel curves

(b) Linearly time normalised TVel curves

(c) Nonlinearly time normalised TVel curves

Figure 4.7: Comparison between (a) original, (b) linearly time normalised (LTN) and (c) nonlinearly time normalised (NTN) TVel curves of the same typical subject as in Figure 4.6. The LTN curves are normalised with movement onset and offset times. NTN curves are normalised via procedure described in Section 4.1 using movement onset, max TVel and movement offset times. Note the inadequacy of the LTN method in this case.

Similarly, Table 4.3 contains a truncated version of the 64 sets of CV for NTN, ORG and LTN. Two-tailed t -tests between means of CV_{NTN} and CV_{ORG} and means of CV_{NTN} and CV_{LTN} results in p -values of 7.1834E-16 and 3.0814E-10 respectively, indicating significant differences between the compared CV means. In fact, 95.31% and 90.63% of the sets of data exhibited lower CV_{NTN} as compared with CV_{ORG} and CV_{LTN} respectively. Taken together, the results from comparisons of SD and CV indicate that data sets subjected to NTN resulted in a significantly lower data variance as compared to ORG and LTN methods. Figure 4.7 shows the effect of NTN and LTN on the same set of data presented in Figure 4.6. Clearly, comparing the variance bounds in Figure 4.7(b) and (c), LTN is unable to remove a large part of the unwanted data variance whereas the NTN method resulted in a much more regular and smaller data variance in this particular set of data. In particular, the double peaks and negative regions of the variance bounds that are also present in the original non-normalised data (Figure 4.7(a)), remain even after LTN (Figure 4.7(b)). These variance bounds seriously compromise the accuracy and reliability of this data set to be used as normative kinematic behaviour for the purpose of assessing pathological movements.

4.3.2.2 Effects of NTN and LTN on performance of EM_TVel curve

Next, whether the NTN procedure results in EM_TVel curves that are more representative of the TVel curves than those obtained from ORG and LTN methods are investigated by using the (i) Pearson product moment correlation ($PPMC$) with zero lag, (ii) local temporal correlation ($CORT$) and (iii) cross approximate entropy ($cross-ApEn$). A summary of these measures are provided in Table 4.4. More detailed descriptions of these measures are provided in the following three sections. The results of investigation using these measures are found in Section 4.3.2.2.4.

Table 4.4: Summary of $PPMC$, $CORT$ and $cross-ApEn$.

$PPMC$	Provides a measure of global temporal correlation between two time series. Ranges between -1 and 1 with '1' indicating strong positive temporal correlation.
$CORT$	Provides a measure of local temporal correlation between two time series that is not affected by global trend. This measure has the distinct advantage of being able to detect temporal variations within localised regions. Ranges between -1 and 1 with '1' indicating strong positive temporal correlation.
$cross-ApEn$	Provides a measure of the degree of asynchrony between two time series. Lower value indicates lower degree of asynchrony which in turns implies a pair of time series is tightly coupled.

4.3.2.2.1 Pearson product moment correlation (PPMC)

Firstly, Pearson product moment correlation (*PPMC*) with zero lag between each TVel curve (trial) and its corresponding EM_TV el curve is used to assess the degree temporal similarity between the EM_TV el curve and the individual TVel curves in a global sense (Krebs et al, 1999; Derrick and Thomas, 2004). A value close to 1 indicates good positive temporal agreement between the EM_TV el curve and individual TVel curves.

Given 2 time series, $S_1 = (u_1, \dots, u_N)$ and $S_2 = (v_1, \dots, v_N)$,

$$PPMC = \frac{\sum_{i=1}^N (u_i - \bar{u}) * (v_i - \bar{v})}{\sqrt{\sum_{i=1}^N (u_i - \bar{u})^2 * \sum_{i=1}^N (v_i - \bar{v})^2}} \quad (4.13)$$

4.3.2.2.2 Local temporal correlation (CORT)

Secondly, local temporal correlation (*CORT*) between each TVel curve (trial) and its corresponding EM_TV el curve is assessed by means of the formula in Eq 4.14. This form of temporal correlation takes into account of local trends of the two time series in comparison and is global trend effect free (Chouakria-Douzal and Nagabhushan, 2006). Similar to *PPMC*, a value close to 1 indicates good positive temporal agreement.

$$CORT = \frac{\sum_{i=1}^{N-1} (u_{i+1} - u_i) * (v_{i+1} - v_i)}{\sqrt{\sum_{i=1}^{N-1} (u_{i+1} - u_i)^2 * \sum_{i=1}^{N-1} (v_{i+1} - v_i)^2}} \quad (4.14)$$

4.3.2.2.3 Cross approximate entropy (cross-ApEn)

Finally, the amount of asynchrony between individual TVel curves and EM_TV el curve is assessed using the cross approximate entropy (*cross-ApEn*) which is designed as a measure of asynchrony between two time series (Pincus, 2000). Lower value of *cross-ApEn* indicates better synchrony between the pair of signals (curves) under comparison. The following descriptions of *cross-ApEn* are based on work by Pincus (2000). Consider 2 time series u and v with N number of discrete time points such that

$$u = \{u(i): 1 \leq i \leq N\} \quad (4.15a)$$

$$v = \{v(i): 1 \leq i \leq N\} \quad (4.15b)$$

Next, define 2 vector sequences x and y such that

$$x_m(i) = \{u(1+k): 0 \leq k \leq m-1\} \quad (4.16a)$$

$$y_m(i) = \{v(1+k): 0 \leq k \leq m-1\} \quad (4.16b)$$

where $1 \leq i \leq N-m+1$

For example, if $N = 50$ and $m = 2$,

$$x_2(1) = \{u(1), u(2)\}$$

$$x_2(2) = \{u(2), u(3)\}$$

$\vdots$

$$x_2(49) = \{u(49), u(50)\}$$

A distance measure is defined as:

$$d[x_m(i), y_m(j)] = \max \{ |u(i+k) - v(j+k)| : 1 \leq i, j \leq N-m+1, 0 \leq k \leq m-1 \} \quad (4.17)$$

A probability measure is defined as:

$$C_i^m(r)(v \parallel u) = \frac{\text{number of } j \leq N - m + 1 \text{ s.t. } d[x_m(i), y_m(j)] \leq r}{N - m + 1} \quad (4.18)$$

and the average of $\ln[C_i^m(r)(v \parallel u)]$ as:

$$\Phi^m(r)(v \parallel u) = \frac{\sum_{i=1}^{N-m+1} \ln[C_i^m(r)(v \parallel u)]}{N - m + 1} \quad (4.19)$$

Finally,

$$\text{cross-ApEn}(m, r, N)(v \parallel u) = \Phi^m(r)(v \parallel u) - \Phi^{m+1}(r)(v \parallel u) \quad (4.20)$$

In this study, *cross-ApEn* is calculated by setting two parameters, window length, $m = 1$ and tolerance level, $r = 0.2$ (Pincus, 2000). All curves are standardised to have 0 mean and standard deviation 1 before calculating *cross-ApEn*. Pincus (2000) noted that these values of m and r coupled with standardisation of the time series ensure good replicability properties for *cross-ApEn* for time series with 50 or more data points. Note that *cross-ApEn* is not symmetrical, that is, $\text{cross-ApEn}(v \parallel u) \neq \text{cross-ApEn}(u \parallel v)$ in general. In $\text{cross-ApEn}(v \parallel u)$, the time series u is set as the template. The frequency of v patterns that is similar to the u patterns of window length m within a tolerance r is calculated in Eq 4.18. Hence, in this project, for a set of trials, *cross-ApEn* is applied to the EM_TVel curve (v) and each TVel trial (u) in the same set to measure the amount of asynchrony between them. Lower value of *cross-ApEn* indicates better synchrony between the EM_TVel curve and the individual TVel trial curve which in turn is interpreted as higher degree of representativeness of the EM_TVel curve.

4.3.2.2.4 Comparison using PPMC, CORT and cross-ApEn

The means of $PPMC_{ORG}$, $PPMC_{NTN}$, $PPMC_{LTN}$, $CORT_{ORG}$, $CORT_{NTN}$, $CORT_{LTN}$, cross-ApEn_{ORG} , cross-ApEn_{NTN} and cross-ApEn_{LTN} are calculated using 638 trials. The calculation of the mean of $PPMC_{ORG}$ is illustrated in Table 4.5. The remaining means are calculated in the same manner.

Table 4.5: Illustration on the calculation of mean of $PPMC_{ORG}$ using a total of 638 trials (16 subjects each with a maximum of 40 trials). Note that $\sum_{i=1}^{16} n_i = 638$ where n_i denotes the number of trials for i^{th} subject (set). $\text{TVel}_{ORG,1,2}$ denotes the tangential velocity of the original (ORG) condition, set 1 and trial 2. $\text{EM_TVel}_{ORG,1}$ denotes the ensemble mean tangential velocity of the ORG condition and set 1.

Set (i)			
1	$\text{TVel}_{ORG,1,1}$ $\text{TVel}_{ORG,1,2}$ $\vdots$ $\text{TVel}_{ORG,1,n_1}$	$\text{EM_TVel}_{ORG,1}$ $= \frac{\sum_{j=1}^{n_1} \text{TVel}_{ORG,1,j}}{n_1}$	$[\text{TVel}_{ORG,1,1}, \text{EM_TVel}_{ORG,1}] \rightarrow PPMC_{ORG,1,1}$ $[\text{TVel}_{ORG,1,2}, \text{EM_TVel}_{ORG,1}] \rightarrow PPMC_{ORG,1,2}$ $\vdots$ $[\text{TVel}_{ORG,1,n_1}, \text{EM_TVel}_{ORG,1}] \rightarrow PPMC_{ORG,1,n_1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
16	$\text{TVel}_{ORG,16,1}$ $\text{TVel}_{ORG,16,2}$ $\vdots$ $\text{TVel}_{ORG,16,n_{16}}$	$\text{EM_TVel}_{ORG,16}$ $= \frac{\sum_{j=1}^{n_{16}} \text{TVel}_{ORG,16,j}}{n_{16}}$	$[\text{TVel}_{ORG,16,1}, \text{EM_TVel}_{ORG,16}] \rightarrow PPMC_{ORG,16,1}$ $[\text{TVel}_{ORG,16,2}, \text{EM_TVel}_{ORG,16}] \rightarrow PPMC_{ORG,16,2}$ $\vdots$ $[\text{TVel}_{ORG,16,n_{16}}, \text{EM_TVel}_{ORG,16}] \rightarrow PPMC_{ORG,16,n_{16}}$
			$\text{Mean of } PPMC_{ORG} = \frac{\sum_{i=1}^{16} PPMC_{ORG,i,n_i}}{\sum_{i=1}^{16} n_i}$

These means are then compared using 1-tail paired-sample t -test with the null hypothesis that they are equal against the following 6 alternate hypotheses:

- (i) Mean of $PPMC_{NTN} > \text{Mean of } PPMC_{ORG}$
- (ii) Mean of $PPMC_{NTN} > \text{Mean of } PPMC_{LTN}$
- (iii) Mean of $CORT_{NTN} > \text{Mean of } CORT_{ORG}$
- (iv) Mean of $CORT_{NTN} > \text{Mean of } CORT_{LTN}$
- (v) Mean of $cross-ApEn_{NTN} < \text{Mean of } cross-ApEn_{ORG}$
- (vi) Mean of $cross-ApEn_{NTN} < \text{Mean of } cross-ApEn_{LTN}$

The results of these tests are summarised in Table 4.6. From Table 4.6, it is clear that mean $PPMC_{NTN}$ is significantly higher (closer to 1) than both mean $PPMC_{ORG}$ and $PPMC_{LTN}$. This indicates that the EM_TV_{el} curves obtained via NTN have higher level of global temporal correlation with their respective sets of individual TV_{el} curves. Similarly, mean $CORT_{NTN}$ is significantly higher (closer to 1) than both mean $CORT_{ORG}$ and $CORT_{LTN}$. In this case, this result indicates that the EM_TV_{el} curves obtained via NTN have higher level of local temporal correlation with their respective sets of individual TV_{el} curves. In other words, the EM_TV_{el} curves obtained via NTN procedure explain or track both the global and local temporal trends of their respective sets of TV_{el} curves more accurately.

The significantly lower value of mean $cross-ApEn_{NTN}$ (Table 4.6) in comparison to both mean $cross-ApEn_{ORG}$ and mean $cross-ApEn_{LTN}$ indicates that the EM_TV_{el} curves obtained via NTN are more synchronous with their respective sets of individual TV_{el} curves. A higher degree of synchronicity between the EM_TV_{el} curves and their respective sets of individual TV_{el} curves indicates that the EM_TV_{el} curves obtained via NTN procedure are more tightly coupled with the individual TV_{el} curves. Hence, these NTN EM_TV_{el} curves are more capable of tracking changes in the individual TV_{el} curves than both the ORG and LTN EM_TV_{el} curves.

All in all, these results suggest that the NTN method resulted in EM_TV_{el} curves that are more representative of the 64 data sets, on the whole, than that obtained via both the ORG and LTN methods.

Table 4.6: Mean (638 trials) of Pearson product moment correlation (*PPMC*), temporal correlation (*CORT*) and cross approximate entropy (*cross-ApEn*) of individual trials and corresponding mean ensemble curves. Values in parentheses are the *p*-values of 1-tailed paired-sample *t*-test comparing against NTN method.

	NTN	ORG	LTN
<i>PPMC</i>	0.9924 ± 0.0103	0.9664 ± 0.0555 (1.4306E-30)	0.9801 ± 0.0102 (1.8213E-18)
<i>CORT</i>	0.9820 ± 0.0208	0.9445 ± 0.0732 (1.2062E-38)	0.9678 ± 0.0500 (2.3926E-15)
<i>cross-ApEn</i>	0.3320 ± 0.0808	0.3400 ± 0.0901 (0.0002)	0.3363 ± 0.0857 (0.0058)

4.4 Concluding remarks

The NTN procedure proposed in this chapter (Section 4.1) is applied successfully to normalise the time of TVel curves obtained from experiments in Chapter 3. Though not aimed at reducing or minimising data variance, data sets in this project subjected to NTN procedure incidentally exhibited lower amount of data variance (Table 4.2 and 4.3). More importantly, in the context of this project, the variance bounds resulting from NTN procedure are more regular with lesser negative regions, thus suggesting a reduction of unwanted temporal variance that may contaminate the actual amplitude variance (Section 4.3.2.1). Lastly, the EM_TV_{el} curves obtained via NTN procedure have also been shown to be more representative of the corresponding sets of individual TV_{el} curves (Section 4.3.2.2). However, it is noted that the extent of this improvement (as assessed by increases in *PPMC* and *CORT* as well as a decrease in *cross-ApEn* in Table 4.6) may not seem substantial enough to make a practical difference. In other words, these results appear to suggest that, in general, the LTN method may suffice if the main objective is only to obtain a representative EM_TV_{el} behaviour. On the other hand, the practical value of the changes in these parameters is difficult to determine at the current stage of this project. For example, the *CORT* parameter will be used in Chapter 7 to determine one of the thresholds that defines normal reach-to-grasp movement (the vertical dashed lines in Figures 7.10 and 7.11). When the LTN method is used, the expected decrease in mean and an increase in standard deviation of *CORT* will increase the ‘normal’ area. Whether such an increase will result in false negatives (patients wrongly diagnosed as ‘normal’) is in itself a challenging clinical question to answer. Consequently, the clinical benefit of applying NTN over LTN can only be determined with extensive clinical trials as part of future work.

Recall that the objective of this chapter is to propose a novel landmark based registration procedure that will achieve proper time normalisation of hand transport TVel curves while preserving the temporal correspondence between kinematic events of the hand transport, forearm supination and grasping components. Besides achieving more representative EM_TVel curves, the NTN procedure also implements novel Step 4 and 6 (Section 4.1) which preserves the temporal correspondence between kinematic events of the hand transport, forearm supination and grasping components. Essentially, Step 4 performs curve registration (time normalization) on the 3D position data which is then used to derive all the hand transport, forearm supination and grasping kinematics. The preservation of temporal correspondence is thus a direct consequence of this procedure. However, time normalisation of 3D position domain does not always result in properly aligned hand transport TVel curves in one step. Hence, the NTN is an iterative procedure which then implements Step 6 as a termination criterion. In a nutshell, Step 6 seeks to detect a lack of change in hand transport TVel amplitude variance in consecutive iterations which serves to indicate that further curve registration is no longer needed in order to avoid ‘over-registration’. In conclusion, the NTN procedure fulfils the objective of this chapter and allows investigations to be performed to determine the effects of forearm supination and grasping on hand transport TVel (Chapter 5).

As the NTN procedure is based on the landmark registration method, it necessarily inherits the limitations of landmark registration method. Expectedly, NTN can only be implemented if a common set of identifiable and distinguishable landmarks exists on all curves to be registered. Fortunately, in this study, all the hand transport TVel curves obtained from the normal healthy subjects contain easily identifiable and distinguishable landmarks.

Another limitation of the NTN method is related the locations of the landmarks. When landmarks are located too close together, they can potentially result in warping functions with high gradient regions. This will in turn cause large change in TVel amplitude (Eq 4.9) thus changing the morphology of the TVel curve. One possible solution may involve imposing upper and lower gradient limits on the nonlinear warping function at each iteration. The challenge then becomes that of determining these limits. Once again, fortunately, in this study, the three chosen landmarks are well separated temporally.

The calculation of target locations for landmarks in Step 2 is performed by computing the mean time of occurrences of the identified landmarks. As mean is sensitive to outliers, the

existence of outlying curve can similarly exert a strong influence on the computed target location, especially so when the number of curves is small. In the context of curve registration, an outlying curve is defined to be one that contains outlying landmarks. Consider a set of n curves with three landmarks each, $\{(L_{1,1}, L_{1,2}, L_{1,3}), (L_{2,1}, L_{2,2}, L_{2,3}) \dots (L_{n,1}, L_{n,2}, L_{n,3})\}$, and assume that the n th curve is the outlying curve with $L_{n,2}$ and $L_{n,3}$ being the outlying landmarks. In the first type of outlying curve, both $L_{n,2}$ and $L_{n,3}$ are either much smaller or larger than the rest of the landmarks, thus, influencing the second and third target landmark locations in the same direction and magnitude. In this case, the warping functions of these curves will be approximately linear and therefore changes in morphology of the registered curves are small. In the second type of outlying curve, the second and third target landmark locations are influenced either (i) in the same direction but of different magnitude or (ii) in the different direction but of same magnitude or (iii) in the different direction and magnitude. In such cases, warping functions may consist of high gradient regions which in turn will result in large change of TVel amplitude (Eq 4.9) thus changing the morphology of the TVel curve. When such situations arise, it is advisable to exclude the outlying curve from the curve registration process. Recall that in this study, the NTN procedure is applied to perform time normalization at the intra-subject level. Therefore, most of the outlying curves encountered belong to the first type and those of the second type do not result in warping functions with excessively high gradient regions. Hence, the morphology of the curves is not drastically changed in such a way that an originally single peak bell shaped curve is changed to a double peak curve.

Chapter 5

Identifying Forearm Supination and Grasping Kinematic Events that Affect Normal Reach-to-grasp Transport Tangential Velocity

The NTN procedure proposed in Chapter 4 clearly demonstrates the importance of aligning important kinematic events in the time normalisation of hand transport TVel profiles.

However, only kinematic events derived directly from the hand transport TVel profile are used as temporal landmarks. Recall that the actual reach-to-grasp tasks (CYL and CUBE), which will be used for actual assessment of stroke patients' UE performance (Chapter 7), consist of 3 main movement components, namely, (i) hand transport, (ii) orientation (forearm supination) and (iii) grasping. It is therefore believed that any forearm supination and grasping kinematic events that exert significant influence on the hand transport TVel profile should also be aligned, if feasible, during the time normalisation of the hand transport TVel profiles.

It has been concluded through literature review (Section 2.5) that these 3 components are interdependently executed. In fact, changes in either orientation or grasping have been shown to affect the hand transport TVel profile. Therefore, it is logical to expect the hand transport TVel profiles for the TOU, SUP, CYL and CUBE tasks (Section 3.2) to be different. Even so, the expected differences in hand transport TVel profiles shall not be assumed, but will be investigated rigorously in this chapter. This investigation is facilitated by the design of the experiment (Section 3.2) as well as the NTN procedure (Chapter 4) which preserves the corresponding temporal relationships between the 3 movement components.

Hence the main objective of this chapter is to identify forearm supination and grasping kinematic events that exert significant influence on the hand transport TVel profile.

Subsequently, in Chapter 6, it will then be determined if it is feasible to use these identified kinematic events to perform further temporal alignment for the sets of TVel curves that have been subjected to NTN procedure. In order to fulfil the objective, the followings shall be accomplished in this chapter:

- 1) The hand transport TVel profiles of the 4 experiment tasks shall be assessed statistically and quantitatively so as to determine if the differences are significant. This will be performed using the TVel profiles over the entire movement duration

instead of specific kinematic parameters. In this study, this is also known as the global investigation.

- 2) Post-hoc analyses of common kinematic parameters such as maximum TVel amplitude, time to peak TVel, average TVel amplitude, approach velocity, temporal smoothness and spatial smoothness have been used to characterise a hand transport TVel profile. In this study, changes in these parameters will also be evaluated to provide a better understanding on specific changes in the hand transport TVel profiles.
- 3) Lastly, differences between a pair of hand transport TVel profiles will be determined at regular time interval throughout the entire movement duration. In this way, time intervals with prominent increase in TVel amplitude difference can be identified. Finally, it shall be determined if these intervals are associated with the occurrences of specific forearm supination and grasping kinematic events. In this study, this is also known as the local investigation.

5.1 Upper extremity model definition and angle calculation

In order to estimate the forearm supination kinematics, an upper extremity (UE) model is defined according to the recommendations by International Society of Biomechanics (Wu et al., 2005). The time normalised 3D position data from the anatomical landmark markers (Figure 3.1) on the UE are used to define the axes vectors for the upperarm and forearm.

Referring to Figure 5.1, the upperarm orthogonal axes are defined as follow:

- 1) Calculate the mid-point (VE) between ME and LE and define the Z axis as the vector $\overrightarrow{(AC - VE)}$.
- 2) Define a temporary X axis (X_{temp}) as the vector $\overrightarrow{(LE - ME)}$.
- 3) Calculate the Y axis as $(Z \times X_{temp})$. In this way, the Y axis is perpendicular to the plane defined by AC, ME and LE.
- 4) Calculate the final X axis as $(Y \times Z)$.

Figure 5.1: Definition of upperarm axes. AC: acromium marker; ME: medial epicondyle marker; LE: lateral epicondyle marker; VE: virtual marker that is mid-point of ME and LE.

Referring to Figure 5.2, the forearm orthogonal axes are defined as follow:

- 1) Calculate the mid-point (VE) between ME and LE and define the Z axis as the vector $\overrightarrow{(VE - US)}$.
- 2) Define a temporary X axis (X_{temp}) as the vector $\overrightarrow{(RS - US)}$.
- 3) Calculate the Y axis as ($Z \times X_{temp}$). In this way, the Y axis is perpendicular to the plane defined by ME, LE, RS and US.
- 4) Calculate the final X axis as ($Y \times Z$).

Figure 5.2: Definition of forearm axes. ME: medial epicondyle marker; LE: lateral epicondyle marker; VE: virtual marker that is mid-point of ME and LE; RS: radius styloid process marker; US: ulnar styloid process marker.

The forearm coordinate system is set relative to the upperarm coordinate system using these defined axes (Figures 5.1 and 5.2). Forearm flexion-extension, abduction-adduction and supination-pronation axes are defined as X, Y and Z respectively. The forearm supination-pronation angle, relative to the upperarm, is obtained via the XYZ rotation sequence as the Z axis rotation angle. Then, forearm supination-pronation angle and angular velocity are calculated, using the forward difference method, for each trial. Again, a point-by-point ensemble mean supination-pronation angular velocity is obtained for each of the 4 different tasks for each subject.

5.2 Methods for hand transport EM_TV_{el} curves comparisons

All 64 sets (16 subjects $\times$ 4 tasks) of experimental data obtained in Chapter 3 are subjected to time normalisation via the NTN procedure proposed in Chapter 4 (refer to Appendix A for illustrations of time normalising of hand transport TV_{el} profiles for the 4 tasks for a single typical subject). In the NTN procedure, time normalisation is performed in the 3D position domain so as to preserve the corresponding temporal relationship between the hand transport, forearm supination and grasping movement components after time normalisation. This is performed for each data set independently. The time normalised 3D position data is then used to calculate the time normalised hand transport TV_{el} using the forward difference method. These time normalised hand transport TV_{els} are then used to obtain a point-by-point hand transport EM_TV_{el} curve for each of the 4 different tasks (TOU, SUP, CYL and CUBE) for each subject. That is, for each subject, there are 4 hand transport EM_TV_{el} curves representing his average hand transport TV_{el} profile during performance of each of the 4 tasks (Figure 5.3).

In order to compare hand transport EM_TV_{el} curves of the 4 different tasks, both global and local investigations are performed. Global investigation takes into account the general trend, characteristics and behaviour of the hand transport EM_TV_{el} curves over the entire movement duration. Local investigations focus on comparing the hand transport EM_TV_{el} curves over smaller and more localised regions of the entire movement duration. To enable comparison across the 4 different tasks, all hand transport EM_TV_{el} curves are further normalised with maximum movement duration as 100% (Figure 5.3). All curves are then interpolated between 0% and 100% at regular interval of 1% using cubic spline. That is, there are 101 data points on each hand transport EM_TV_{el} curve. Refer to Appendix B for such plots for all subjects.

Figure 5.3: Comparison of hand transport EM_TVel curves for the 4 different tasks for a typical subject. Blue: TOU; Red: SUP; Magenta: CYL and Black: CUBE. Note that all EM_TVel curves are further normalised to 100% movement duration to enable comparisons to be made.

The list of measures to be used in comparing the hand transport EM_TVel curves for the 4 different tasks is summarised in Table 5.1. Note that for both global and local investigations, these measures are further categorised as ‘non-kinematic’ and ‘kinematic’. The ‘non-kinematic’ measures simply compare the EM_TVel curves based on curve characteristics which do not bear kinematic meaning with respect to the movement under investigation. The ‘kinematic’ measures, on the other hand, assess the difference between the EM_TVel curves based on specific kinematic parameters that are relevant the movement under investigation. More detailed descriptions of these measures are provided in Sections 5.2.1 and 5.2.2. The results and discussions of these comparisons are presented in Section 5.3.

Table 5.1: A summary of measures used for comparing hand transport EM_TV_{el} curves across all 4 experimental tasks.

<p><u>Global measures</u></p> <p><i>Non-kinematic:</i></p> <ol style="list-style-type: none"> 1) Adaptive Neyman (ANey) test (Fan and Lin, 1998) 2) Discrete Frechet distance (DFD) (Eitner and Mannila, 1994) 3) Summed discrete Frechet distance (SDFD) 4) Kullback-Leibler divergence measure (KL) (Csiszar, 1991) <p><i>Kinematic:</i></p> <ol style="list-style-type: none"> 1) Normalised jerk metric (Teulings et al, 1997) 2) MedianLC (Osu et al, 2011) 3) Average velocity 	<p>A statistical test that is designed to determine if differences in 2 EM_TV_{el} curves are statistically significant. The key feature of this test lies in the fact that it uses the entire curve for comparison thus avoiding the pitfall of curve comparison techniques that are based on single parameter which describes only a micro aspect of the entire time series curve.</p> <p>A maximum measure that is designed to assess degree of shape similarity between 2 discretized curves. The DFD algorithm creates a free space containing distances between possible combinations of points from 2 discrete time series curves. The maximum distance within this free space is the DFD. The main shortcoming of this measure is its sensitivity towards outliers.</p> <p>A new measure proposed in this study to address the main shortcoming of DFD. This is achieved by identifying the set of distances within the free space containing the DFD value that results in a minimum sum.</p> <p>Measures how well one function estimates another. Note that this can only be applied to non-negative function.</p> <p>A measure of temporal smoothness of movement. Higher jerk value indicates lower level of temporal smoothness.</p> <p>A measure of spatial smoothness of movement. This is based on the curvature of movement trajectory. Higher MedianLC value indicates higher level of spatial smoothness.</p> <p>A gross measure of the hand transport TV_{el} amplitude.</p>
<p><u>Local measures</u></p> <p><i>Non-kinematic:</i></p> <ol style="list-style-type: none"> 1) Components of KL divergence measures <p><i>Kinematic:</i></p> <ol style="list-style-type: none"> 1) Approach velocity 2) Relative timing of max EM_TV_{el} 3) MaxLag 	<p>A comparison of 2 time series curves at each discrete time point using the components of KL divergence measures. This is aimed at identifying localised regions where big discrepancies between 2 curves occur.</p> <p>Defined to be the average hand transport TV_{el} for the last 10% of movement.</p> <p>The time of occurrence of maximum EM_TV_{el} is taken as a gross measure of symmetry of the EM_TV_{el} curve.</p> <p>Lag to achieve maximum Pearson product moment correlation (PPMC) (Derrick & Thomas, 2004) between EM_TV_{el}s of different tasks. This is used to estimate the amount of difference in temporal symmetry between 2 EM_TV_{el} curves.</p>

5.2.1 Global investigation

For global investigation, adaptive Neyman (ANey) statistic (Fan & Lin, 1998), discrete Frechet distance (DFD) (Eiter & Mannila, 1994) and Kullback-Leibler (KL) divergence measure are used to assess if hand transport EM_TVel curves between the 4 different tasks are different on a global level. These are then followed by analyses on how hand transport EM_TVel curves' amplitude and temporal characteristics as well as movement smoothness are affected.

5.2.1.1 Adaptive Neyman (ANey) test

Chau et al. (2005) adapted the ANey test to compare gait data and recommended that curve comparisons be based on the entire curve before performing landmark analysis and simple parameterizations as meaningful post-hoc procedure. In this study, the ANey test proposed by Fan and Lin (1998) shall be implemented to compare pairs of hand transport EM_TVel curves. The main ANey steps are described here for easy reference:

Given two sets of TVel time series curves $\{X_i(k)\}_{k=1}^T$ and $\{Y_j(k)\}_{k=1}^T$ where $1 \leq i \leq N_X$, $1 \leq j \leq N_Y$, K is the number of discrete time points and N_X and N_Y are the number of TVel curves (individual trials) for the first and second set respectively. The null hypothesis of the ANey test is that the difference between the means (EM_TVel) of these two sets of curves is zero.

First, all the individual TVel curves in each set are subjected to discrete Fourier transform via the Fast Fourier Transform algorithm. This is implemented with the 'fft' function in Matlab. Let $\{X_i^*(k)\}_{k=1}^T$ and $\{Y_j^*(k)\}_{k=1}^T$ denote the sets of Fourier transformed TVel curves. $X_i^*(1)$ is the real part at the 0th Fourier frequency, $X_i^*(2)$ is the real part at the 1st Fourier frequency, $X_i^*(3)$ is the imaginary part at the 1st Fourier frequency, and so on.

Hence the sample means of these sets of coefficients are defined as

$$\overline{X^*(k)} = \frac{\sum_{i=1}^{N_X} X_i^*(k)}{N_X}, \quad 1 \leq k \leq T \quad (5.1a)$$

$$\overline{Y^*(k)} = \frac{\sum_{i=1}^{N_Y} Y_i^*(k)}{N_Y}, \quad 1 \leq k \leq T \quad (5.1b)$$

Then the difference of sample means in the frequency domain is defined as

$$D^*(k) = \overline{X^*(k)} - \overline{Y^*(k)} \quad (5.2)$$

and the standardised difference is

$$Z(k) = \frac{D^*(k)}{\sqrt{\left(\frac{\sigma_X^2(k)}{N_X} + \frac{\sigma_Y^2(k)}{N_Y}\right)}} \quad (5.3)$$

where $\sigma_X^2(k)$ and $\sigma_Y^2(k)$ are the variance estimators of the first and second sets of TVel curves respectively.

Next, a cutoff frequency (c_T) is defined based on the frequency components of the Fourier transformed TVel curves so as to remove the high frequency noise components. Hence, Fourier transformation serves the dual purposes of decorrelating and filtering off the high frequency noise of human motion time series data. In this study, the absolute values of the Fourier coefficients for all TVel curves in each experimental task (TOU, SUP, CYL and CUBE defined in Chapter 3) are plotted. These plots of a typical subject whose data required a higher cutoff frequency than most other subjects are shown in Figure 5.4 (such plots for all subjects are found in Appendix C-1). In Figure 5.4, the absolute values of Fourier coefficients for all TVel curves in each of the 4 experimental tasks are observed to approach zero beyond the 19th coefficient. Hence, in this study, $c_T = 19$ is used as the cutoff frequency for all subjects.

The ANey test is defined as

$$T_{AN}^* = \max_{1 \leq m \leq c_T} (2m)^{-\frac{1}{2}} \sum_{k=1}^m (|Z(k)|^2 - 1) \quad (5.4)$$

Finally the standardised ANey is defined as

$$T_{AN} = \sqrt{2 \ln \ln c_T} T_{AN}^* - (2 \ln \ln c_T + 0.5 \ln \ln \ln c_T - 0.5 \ln(4\pi)) \quad (5.5)$$

The ANey test is equivalent to rejecting the null hypothesis when T_{AN} is too large. Fan and Lin (1998) noted that the asymptotic distribution of the distribution of T_{AN} under the null hypothesis is given by

$$P(T_{AN} \leq x) \rightarrow e^{-e^{-x}} \quad (5.6)$$

and provided a finite sample distribution of the distribution of T_{AN} under the null hypothesis based on 1 million simulations. Suffice to note that the p -values of the ANey tests in this study are calculated based on these results (refer to Appendix C-2 for a detailed description).

(a)

(b)

Figure 5.4: Absolute Fourier coefficients amplitude of all TVel curves for each of the 4 tasks (blue: TOU; red: SUP; magenta: CYL; black: CUBE) for a typical subject. Vertical axis denotes the absolute coefficient amplitude. Horizontal axis denotes the n th coefficient. The arrow indicates the number of coefficients used. (a) Note that this subject requires higher number of coefficients compared with all other subjects and that the coefficient amplitude is negligible after the 19th coefficients. (b) A magnified version of (a).

5.2.1.2 Discrete Frechet distance (DFD) & Sum DFD (SDFD)

The original Frechet distance is a similarity measure between two continuous curves. The main concept behind Frechet distance has frequently been illustrated in a ‘dog-man’ distance example. Imagine a man walking a dog on a leash. The man and dog move along their own paths at their own speed without back tracking. For every such walk, along the same respective paths, a maximum leash length can thus be recorded. By considering all possible such walks, the Frechet distance is defined as the minimum of all possible maximum leash length from these walks.

Given two continuous curves $f: [a, b] \rightarrow W$ and $g: [a', b'] \rightarrow W$ where $a, b, a', b' \in \mathbb{R}$ and $a \leq b, a' \leq b'$ and (W, d) is a metric space, their Frechet distance is defined as

$$\delta_F(f, g) = \inf_{\alpha, \beta} \max_{t \in [0, 1]} d(f(\alpha(t)), g(\beta(t))) \quad (5.7)$$

where α and β are arbitrary continuous non-decreasing functions from $[0, 1]$ onto $[a, b]$ and $[a', b']$ respectively and d is a distance measure between f and g .

The main advantage of Frechet distance is that it takes into account both the location and ordering of points on both curves (Eiter & Mannila, 1994) but can be computationally very intensive. In this study, a computationally more efficient algorithm for calculating discrete Frechet distance (DFD) for polygonal curves proposed by Eiter and Mannila (1994) that is also known as the coupling distance shall be implemented.

Given two time series with discrete time points $P = (u_1, \dots, u_p)$ and $Q = (v_1, \dots, v_q)$, define a sequence of m pairs of couplings between these two sets of time points:

$(u_{a_1}, v_{b_1}), (u_{a_2}, v_{b_2}), \dots, (u_{a_m}, v_{b_m})$ such that $a_1 = 1, b_1 = 1, a_m = p, b_m = q$ and $a_{i+1} = a_i$ or $a_{i+1} = a_i + 1$ for $i = 1, \dots, p$ and $b_{j+1} = b_j$ or $b_{j+1} = b_j + 1$ for $j = 1, \dots, q$. In this way, these couplings will respect the order of points in P and Q as well as ensure that the sequence is non-decreasing. The DFD is then defined as

$$\delta_{dF}(P, Q) = \min \left(\max_{t=1, \dots, m} d(u_{a_t}, v_{b_t}) \right) \quad (5.8)$$

The algorithm essentially seeks the DFD from an array of Euclidean distances for each point on one curve to all points on the other curve. An example is illustrated in Figure 5.5. Figure 5.5a shows two polygonal curves with vertices marked by open circles. Figure 5.5b contains the Euclidean distances between pairs of vertices on the two curves. That is $d(B1, R1) = 0.5$ is the distance between the first vertices on the red and blue curves, $d(B2, R1) = 1.5$ is the distance between the second blue curve vertex and the first red curve vertex, and so on. The DFD algorithm is equivalent to traversing from (B1, R1) to (B9, R10) in the same manner described in the above ‘dog-man’ example. The result of this algorithm is a free space that outputs the maximum value in this free space as the DFD (Figure 5.5c).

In this study, the DFD algorithm is implemented to determine the similarity between EM_TV_{el} curves of two different experimental tasks. Recall that the horizontal axes of all the EM_TV_{el} curves have been normalised to 100%. In order to calculate the Euclidean distances, the amplitude of each EM_TV_{el} curve (vertical axis) for each subject is also normalised to the maximum amplitude among the 4 EM_TV_{el} curves of that subject. In this way, both axes are expressed in percentages with maximum at 100%.

However, the DFD is essentially a form of maximum measure that can be distorted by isolated localised large differences between two curves (Figure 5.6a). Furthermore, it is also sensitive to small variations in input values (sampled points on the curves) leading to non-robust behaviour (Efrat et al., 2007) (Figure 5.6b). Devogele (2002) proposed averaging along a path with minimum summed distances within the free space that contains the DFD. However, the path identification procedure outlined may not be optimal. In this study, the Dijkstra's graph search algorithm is implemented to identify the set of ordered pairs of points on two curves that gives the minimum summed distance. It is important to emphasize that the Dijkstra's algorithm has to be applied in the reduced free space resulting from DFD algorithm. As shown in Figure 5.7a, the orange highlighted path is the result of applying the Dijkstra's algorithm in the original space. Note that this path does not contain the desired DFD. When applied correctly in the reduced free space as in Figure 5.7b, the yellow highlighted path contains the desired DFD. It is verified, without providing mathematical proof, that all these paths in the results in this study contain the DFD. This minimum summed distance is referred to as SDFD and will be used to supplement DFD analysis on the geometric similarity between two curves.

(a)

	B1	B2	B3	B4	B5	B6	B7	B8	B9
R1	0.5	1.5	2.5	3.6401	6.7268	7.433	6.5765	7.5	13.124
R2	1.6	0.4	1.4	2.6	6.0465	6.6603	5.4918	6.4	12.44
R3	4.4721	4	4.1231	3.6056	3.1623	4.1231	5.831	7.2111	9.2195
R4	5	4.1231	4	3.1623	2.2361	3.1623	5	6.4031	8.4853
R5	10.77	10.198	10.05	9	5.099	5.3852	9.4868	10.77	5
R6	5	3	2	1.4142	5	5.099	2.2361	3	10.77
R7	6.7082	5	4.2426	2.8284	2.2361	2	2.2361	3.6056	7.6158
R8	7.2801	5.3852	4.4721	3.1623	3.6056	3.1623	1	2.2361	8.2462
R9	8.0623	6.0828	5.099	4	5	4.4721	1	1	9.0554
R10	13.454	12.207	11.662	10.296	6.4031	5.831	9.2195	10.05	0

(b)

	B1	B2	B3	B4	B5	B6	B7	B8	B9
R1	0.5	1.5	2.5	3.6401					
R2	1.6	0.4	1.4	2.6					
R3	4.4721	4	4.1231	3.6056	3.1623	4.1231			
R4	5	4.1231	4	3.1623	2.2361	3.1623			
R5					5.099				
R6					5				
R7					2.2361	2	2.2361	3.6056	
R8					3.6056	3.1623	1	2.2361	
R9					5	4.4721	1	1	
R10									

(c)

Figure 5.5: Illustration of discrete Frechet distance (DFD) algorithm proposed by Eiter and Mannila (1994). (a) Two polygonal curves with vertices indicated by open circles. (b) An array of Euclidean distances between all vertices on the two polygonal curves. Distance between 1st points on each curves is $d(B1, R1) = 0.5$ and so on. (c) The remaining white cells are the free space resulting from DFD algorithm. The maximum value (5.099) in this free space is the DFD.

Figure 5.6: Illustration of DFD shortcoming. The two continuous curves are ‘converted’ to polygonal curves by sampling a finite set of points on each curve. (a) Illustrates the distortion in DFD caused by a single point on one curve that is a very large distance away. (b) Illustrates the effect of sampling where the point with a large influence is not selected.

	B1	B2	B3	B4	B5	B6	B7	B8	B9
R1	0.5	1.5	2.5	3.6401	6.7268	7.433	6.5765	7.5	13.124
R2	1.6	0.4	1.4	2.6	6.0465	6.6603	5.4918	6.4	12.44
R3	4.4721	4	4.1231	3.6056	3.1623	4.1231	5.831	7.2111	9.2195
R4	5	4.1231	4	3.1623	2.2361	3.1623	5	6.4031	8.4853
R5	10.77	10.198	10.05	9	5.099	5.3852	9.4868	10.77	5
R6	5	3	2	1.4142	5	5.099	2.2361	3	10.77
R7	6.7082	5	4.2426	2.8284	2.2361	2	2.2361	3.6056	7.6158
R8	7.2801	5.3852	4.4721	3.1623	3.6056	3.1623	1	2.2361	8.2462
R9	8.0623	6.0828	5.099	4	5	4.4721	1	1	9.0554
R10	13.454	12.207	11.662	10.296	6.4031	5.831	9.2195	10.05	0

(a)

	B1	B2	B3	B4	B5	B6	B7	B8	B9
R1	0.5	1.5	2.5	3.6401					
R2	1.6	0.4	1.4	2.6					
R3	4.4721	4	4.1231	3.6056	3.1623	4.1231			
R4	5	4.1231	4	3.1623	2.2361	3.1623	5		
R5					5.099				
R6					5	5.099	2.2361	3	
R7					2.2361	2	2.2361	3.6056	
R8					3.6056	3.1623	1	2.2361	
R9					5	4.4721	1	1	
R10									0

(b)

Figure 5.7: Illustration of finding the least summed path that contains the DFD. (a) Illustrates the scenario when Dijkstra’s algorithm is wrongly applied to the original distance space. The orange highlighted path is the shortest summed path (19.9989) but does not contain the desired DFD value (5.099). (b) Dijkstra’s algorithm is applied to the reduced free space. Note that the shortest summed path (highlighted in yellow) in this free space is longer at 22.24, but it correctly contains the DFD value as its maximum.

5.2.1.3 Kullback-Leibler (KL) divergence measure

The Kullback-Leibler (KL) divergence measure, in its original form, is meant to measure the amount of information loss when estimating one probability distribution by another. Csiszar (1991) extended the original definition by introducing the term $\sum(v_i - u_i)$. In this study, this formula shall be referred to as the KL divergence measure:

$$KL(v, u) = \sum u_i \ln(u_i/v_i) - u_i + v_i \quad (5.9)$$

This KL divergence measure enables comparison between two non-negative functions whose components (u_i and v_i) do not have to sum to one (Boyd and Vandenberghe, 2004; Martinez et al, 2010). It is important to note that KL divergence measure is not symmetrical. Hence Eq 5.9 is a measure of how well function v estimates function u . Readers familiar with KL divergence may notice that the order of u and v are switched on the left hand side of equation Eq 5.9. This slight change in convention is to adhere to the rest of notations in this study so as to facilitate ease of discussion later.

5.2.1.4 Post-hoc analysis

Next, as post-hoc analysis, kinematic parameters such as (i) maximum EM_TV_{el}, (ii) average EM_TV_{el}, (iii) approach velocity, (iv) relative timing of maximum EM_TV_{el}, (v) lag to achieve maximum Pearson product moment correlation (PPMC) (Derrick and Thomas, 2004) between EM_TV_{els} of different tasks, (vi) overall movement smoothness, (vii) movement smoothness before occurrence of max EM_TV_{el} and (viii) movement smoothness after occurrence of maximum EM_TV_{el} are compared to examine kinematic aspects of EM_TV_{el} that may be different. In this study, the approach velocity is defined to be the average TV_{el} for the last 10% of movement.

The number of lag to achieve maximum PPMC basically measures the number of data point that one curve needs to be shifted in order to achieve maximum PPMC with another curve (Derrick & Thomas, 2004). In this study, MaxLag($u-v$) is used to denote the number of percentage time point curve v needs to be shifted in order to achieve maximum PPMC with curve u . A positive MaxLag($u-v$) value indicates that curve v needs to shift right MaxLag($u-v$) number of percentage time points (Figure 5.8). In other words, this can also be interpreted as curve u being located to the right relative to curve v .

Figure 5.8: Illustration of positive $\text{MaxLag}(u-v)$ value. Curve u (thick) is located to the right relative to curve v (thin). Curve v needs to shift to the right (dashed) to achieve maximum PPMC with curve u .

Movement smoothness is assessed temporally by normalised jerk metric (Teulings et al, 1997) and spatially by median of negative log curvature (MedianLC) (Osu et al, 2011). The normalised jerk metric is calculated by

$$\text{Normalised jerk metric} = \sqrt{0.5 * (D^5/L^2) * \int J^2 dt} \quad (5.10)$$

where D is the time taken for the movement, L is the path length and J is the third derivative of 3D position. The normalised jerk metric is dimensionless and essentially accounts for the amount of changes in acceleration during the course of movement. An increase in movement smoothness is associated with lesser acceleration changes resulting in lower normalised jerk metric value. Hogan and Sternad (2009) compared jerk based measures with and without dimensions and concluded that dimensionless jerk based measures are more reliable in quantifying deviations from smooth movements. On the other hand, MedianLC is proposed by Osu et al. (2011) to assess movement smoothness spatially using instantaneous 3D curvature (κ) at each time point.

$$\kappa^2 = [(\dot{x}^2 + \dot{y}^2 + \dot{z}^2)(\ddot{x}^2 + \ddot{y}^2 + \ddot{z}^2) - (\dot{x}\ddot{x} + \dot{y}\ddot{y} + \dot{z}\ddot{z})^2]/(\dot{x}^2 + \dot{y}^2 + \dot{z}^2)^3 \quad (5.11)$$

Only time points with TVel exceeding 50 mm/s are used. Then, $-\ln$ of these curvatures (κ) are computed and the median of this distribution of $-\ln(\kappa)$ is extracted as MedianLC. Osu et

al (2011) reported that increase in movement smoothness is associated with higher MedianLC value.

On the individual subject level, one-way ANOVA (unbalanced design for subjects with unequal number of trials per condition) is conducted to investigate the effect of the 4 experimental conditions on each of these kinematic parameters per subject. As a group, two-way mixed effect ANOVA with interaction (subject as a random effect and serves as block) experimental design is performed on (i) maximum EM_TV_{el}, (ii) average EM_TV_{el}, (iii) approach velocity, (iv) relative timing of maximum EM_TV_{el}, (v) normalised jerk metric and (vi) MedianLC to determine if they are significantly different across the 4 experimental conditions. Note that with an exception to relative timing of maximum EM_TV_{el}, all other parameters contain replicates (9 or 10 trials per subject per condition). By setting subject as a random effect, the result of this test can then be generalised to the underlying population of subject on the assumption that the random sampling process is unbiased and representative.

Finally, Tukey's honestly significant difference (HSD) criterion ($\alpha = 0.05$) is used to perform simultaneous multiple pair-wise comparisons between all 4 experimental conditions. Hence, for each parameter there are 6 pairs of such comparisons. For the purpose of this study, the focus shall be on 3 main pairs of comparisons, namely (i) SUP-TOU, (ii) CYL-SUP and (iii) CUBE-CYL. The remaining 3 pairs will supplement the analyses of the main comparisons whenever necessary. All ANOVA and HSD tests are performed using STATISTICA Version 10.

5.2.2 Local investigation

The KL divergence measure in Eq 5.9 is closely related to the relative entropy of u_i and v_i which is given by $u_i \ln(u_i/v_i)$ (Boyd and Vandenberghe, 2004). For this reason, the components of KL divergence measure in Eq 5.9, that is $(u_i \ln(u_i/v_i) - u_i + v_i)$ where $i \in \{0, 1, 2, \dots, 100\}$, shall be used to conduct point-by-point local comparisons. That is, it shall be investigated, at each percentage time point, specifically if supination and grasping results in or corresponds to areas of high discrepancy (or information loss) between the hand transport EM_TV_{el} curves of the 4 different tasks. In other words, local maximum in the graphs of $(u_i \ln(u_i/v_i) - u_i + v_i)$ versus i shall be noted.

5.3 Results and discussions

Section 5.2 describes an extensive list of analyses that are aimed at rigorously analysing the influence that forearm supination and grasping exert on the hand transport TVel profile. In this section, the results and discussions of these analyses shall be presented in subsections according to the three main pairs of comparisons namely, (i) SUP-TOU, (ii) CYL-SUP and (iii) CUBE-CYL.

5.3.1 SUP-TOU comparison

Recall that the only difference between the TOU and SUP tasks is that the SUP task includes a natural forearm supination (Section 3.2). It is believed that the influence of forearm supination on the hand transport TVel can be determined by comparing the differences between the hand transport TVel profiles from these two tasks.

Table 5.2: Results of ANey, DFD, SDFD and KL divergence assessments of SUP-TOU, CYL-SUP and CUBE-CYL EM_TV_{el} curves comparisons. The shaded cells indicate no substantial difference detected in the EM_TV_{el} curves comparisons in those cases.

	SUP-TOU				CYL-SUP				CUBE-CYL			
Sub	ANey	DFD	SDFD	KL	ANey	DFD	SDFD	KL	ANey	DFD	SDFD	KL
1	0.00	16.29	547.75	0.42	0.00	9.41	595.66	1.27	0.00	5.60	275.42	0.38
2	0.00	35.42	1923.22	5.89	0.00	12.43	577.63	0.95	0.00	8.80	387.12	0.38
3	0.00	23.22	1026.80	1.61	0.00	15.69	688.34	1.00	0.00	9.05	334.79	0.26
4	0.00	31.24	1531.54	3.61	0.00	5.93	330.84	0.39	0.00	6.79	411.58	0.74
5	0.00	25.35	1239.30	3.46	0.00	9.20	546.97	1.66	0.08	2.37	102.56	0.04
6	0.00	23.94	1232.13	3.17	0.00	3.44	133.84	0.19	0.00	4.96	264.82	0.31
7	0.00	25.83	1177.15	2.17	0.00	8.84	482.00	0.90	0.00	6.60	308.15	0.24
8	0.00	6.91	323.30	0.30	0.00	16.18	910.91	2.67	0.00	7.36	411.78	0.93
9	0.00	32.28	1999.29	7.11	0.00	5.46	171.90	0.26	0.96	1.04	32.04	0.00
10	0.00	21.68	725.12	1.33	0.00	9.01	468.63	1.34	0.30	3.62	148.62	0.10
11	0.00	21.58	1337.74	6.19	0.00	12.99	853.23	4.79	0.00	4.35	219.23	0.35
12	0.00	29.67	1258.10	1.90	0.00	15.19	907.83	2.21	0.01	2.70	153.26	0.05
13	0.00	26.35	1063.47	1.58	0.00	8.06	328.15	0.33	0.00	5.17	295.94	0.37
14	0.00	26.35	1110.69	2.54	0.00	14.59	381.92	0.63	0.00	8.96	579.95	1.17
15	0.00	9.90	558.41	1.07	0.00	8.08	347.24	0.44	0.00	4.25	288.51	0.50
16	0.00	12.45	707.59	2.02	0.00	11.99	574.74	1.04	0.00	5.29	220.84	0.12
Threshold	< 0.05	> 3.7	> 170	> 0.19	< 0.05	> 3.7	> 170	> 0.19	< 0.05	> 3.7	> 170	> 0.19
No. of subjects showing substantial difference	16	16	16	16	16	15	15	15	13	12	12	11

5.3.1.1 Results for global investigation: ANey, DFD, SDFD and KL divergence

With reference to Table 5.2, ANey indicates that all 16 subjects' TOU and SUP EM_TVel curves are statistically significantly different ($p < 0.05$). By setting criteria of >3.7 for DFD and >170 for SDFD to indicate substantial difference, results agree that all 16 subjects' TOU EM_TVel and SUP EM_TVel profiles are geometrically different. That is, the shape of the EM_TVel curves of TOU and SUP are different. Similarly, by setting a threshold of >0.19 for KL divergence measure to indicate substantial difference, again, results agree that all 16 subjects' TOU EM_TVel and SUP EM_TVel profiles are different. Note that these threshold values are arbitrary. However, the fact that it is possible to identify threshold values for DFD, SDFD and KL divergence measures in such a way that they agree with the results of ANey, give more support to believe that the curves under comparison are indeed different.

5.3.1.2 Results for post-hoc analyses of specific kinematic parameters

As a group, SUP maximum EM_TVel, average EM_TVel and approach velocity are statistically significantly lower than that in TOU (Table 5.3). In fact, 16, 16 and 13 subjects exhibited lower maximum EM_TVel, average EM_TVel and approach velocity in SUP as compared to TOU respectively.

Table 5.3: Mean differences for amplitude and temporal parameters between experimental conditions. Two-way ANOVA with tasks as main effect and subject as a random effect. Multiple comparisons are performed using Tukey's HSD for unbalanced design. Red means difference is statistically significant (< 0.05). Negative sign denotes smaller than. For example, for SUP-TOU, the negative sign in maximum TVel denotes that the SUP maximum TVel is lower than TOU maximum TVel.

	Maximum Tvel (mm/msec)	Average Tvel (mm/msec)	Approach Tvel (mm/msec)	Max Tvel Time (%)
SUP-TOU	-0.181435	-0.125199	-0.046211	2.51101
CYL-SUP	0.0232	5.4E-05	-0.019004	-5.40886
CUBE-CYL	-0.026331	-0.012754	0.00582	0.37221
CYL-TOU	-0.158233	-0.125146	-0.065215	-2.89784
CUBE-TOU	-0.184564	-0.1379	-0.059395	-2.52564
CUBE-SUP	-0.003128	-0.0127	-0.013185	-5.03665

The relative timing of maximum EM_TVel is often taken as a gross measure of symmetry of TVel profile. From Figure 5.9, a slight shift to the right (relative to TOU) in SUP's

distribution of relative timing of max EM_TVel with 2 subjects exceeding 57.5% is observed. A more detailed analysis at an individual subject level is then conducted by calculating the i) difference between relative time of maximum EM_TVel in TOU and SUP (Figure 5.10) and ii) MaxLag(SUP-TOU) (Figure 5.11). A total of 5 subjects record a difference greater than 2.5% (Figure 5.10) and MaxLag(SUP-TOU) value of at least 2 (Figure 5.11), indicating that the EM_TVel in SUP is located right relative to the EM_TVel in TOU for these subjects. These corresponded to an increase in relative timing of max EM_TVel of at least 5.7%. However, the number of subjects exhibiting this phenomenon is small. Furthermore, the ANOVA result in Table 5.3 shows that the SUP-TOU comparison for the relative timing of maximum EM_TVel (column 4) is not statistically significant. Thus, there is insufficient evidence to suggest that SUP and TOU hand transport EM_TVel profiles are different in terms of symmetry.

With reference to Table 5.4, as a group, temporal smoothness of the entire movement, before occurrence of maximum EM_TVel and after occurrence of maximum EM_TVel show statistically significant increase in normalised jerk value in SUP (decrease in smoothness). Respectively, 11, 10 and 9 out of 16 subjects exhibited higher normalised jerk values for SUP than for TOU. Results from supplementary comparisons, CYL-TOU and CUBE-TOU, are similar to these. MedianLC of the entire movement and MedianLC before occurrence of maximum EM_TVel decrease statistically significantly in SUP (decrease in spatial smoothness). For MedianLC of the entire movement, 11 out of 16 subjects exhibit lower value for SUP than for TOU. For MedianLC before occurrence of maximum EM_TVel, 16 out of 16 subjects exhibit lower value for SUP than for TOU. However, smoothness after occurrence of maximum EM_TVel shows a statistically significant increase in MedianLC value in SUP (increase in spatial smoothness). In this case, 11 subjects exhibit higher MedianLC value in SUP than in TOU. From CYL-TOU and CUBE-TOU comparisons, the results also indicate significant decrease in spatial smoothness for the entire movement and before occurrence of maximum EM_TVel. In contrast, difference in spatial smoothness after occurrence of maximum EM_TVel is found to lack statistical significance.

	Relative time of maximum EM_TVel (%)			
	TOU	SUP	CYL	CUBE
Mean	47.53	50.04	44.63	45.00
SD	5.98	7.59	6.40	6.95

Figure 5.9: Relative time of maximum EM_TVel (%). The graph shows the distributions of relative time of maximum EM_TVel for each task for the entire group of subjects. The accompanying table contains the means and standard deviations of the relative time of maximum EM_TVel for each task taken over the entire group of subjects.

(a)

(b)

		SUP-TOU	CYL-SUP	CUBE-CYL	CYL-TOU	CUBE-TOU	CUBE-SUP
Left	(< -2.5)	2	12	3	7	7	12
Right	(> 2.5)	5	1	6	2	3	2

Figure 5.10: Distributions of the difference in relative time of maximum EM_Tvel . (a) Distributions of the difference in relative time of maximum EM_Tvel for the 3 main comparisons SUP-TOU, CYL-SUP and CUBE-CYL. (b) Distributions of the difference in relative time of maximum EM_Tvel for the 3 supplementary comparisons CYL-TOU, CUBE-TOU and CUBE-SUP. The accompanying table summarizes the results of the graphs. For example, under SUP-TOU comparison, the relative time of maximum EM_Tvel in SUP of 2 subjects are earlier than the relative time of maximum EM_Tvel in TOU (< -2.5).

(a)

(b)

		SUP-TOU	CYL-SUP	CUBE-CYL	CYL-TOU	CUBE-TOU	CUBE-SUP
Left	(< -1)	3	11	3	8	7	11
Right	(> 1)	5	1	6	3	3	1

Figure 5.11: Distributions of MaxLag . (a) Distributions of MaxLag for the 3 main comparisons SUP-TOU, CYL-SUP and CUBE-CYL. (b) Distributions of MaxLag for the 3 supplementary comparisons CYL-TOU, CUBE-TOU and CUBE-SUP. The accompanying table summarizes the results of the graphs. For example, under SUP-TOU comparison, the SUP EM_TVel of 3 subjects are located to the left of TOU EM_TVel (< -1).

Table 5.4: Mean differences for movement smoothness metrics between experimental conditions. Two-way ANOVA with tasks as main effect and subject as a random effect. Multiple comparisons are performed using Tukey’s HSD for unbalanced design. Red means difference is statistically significant (< 0.05). Jerk is calculated using Eq 5.10 and MedianLC is calculated based on Eq 5.11. “Bef.” and “Aft.” denote the parts of movement before and after the occurrence of maximum EM_TVel respectively. Negative sign denotes smaller than. For example, for SUP-TOU, the negative sign in MedianLC denotes that the SUP MedianLC is lower than TOU MedianLC.

	Jerk	Bef. Jerk	Aft. Jerk	MedianLC	Bef. MedianLC	Aft. MedianLC
SUP-TOU	3.6545	1.27186	0.44428	-0.206083	-0.803601	0.310009
CYL-SUP	3.08349	-0.06066	1.01434	-0.058731	0.11144	-0.214118
CUBE-CYL	-0.35477	0.10939	-0.14354	-0.137596	-0.026536	-0.1793
CYL-TOU	6.73799	1.21121	1.45862	-0.264814	-0.692162	0.095892
CUBE-TOU	6.38322	1.3206	1.31509	-0.402411	-0.718697	-0.083409
CUBE-SUP	2.72873	0.04874	0.87081	-0.196327	0.084904	-0.393418

5.3.1.3 Results for local investigation

Graphs of this point-by-point comparison (Section 5.2.2) for all 16 subjects for SUP-TOU comparison are shown in Figure 5.12. To facilitate discussion, the curves for this pair of comparison are denoted by KL(SUP-TOU) (Figure 5.12). It should be noted that the summation over all the points on a KL(SUP-TOU) curve is equal to the $KL(v_{SUP}, u_{TOU})$ value (Eq 5.9).

Local maxima on the KL(SUP-TOU) curve between the occurrences of maximum forearm supination acceleration and velocity is observed (Figure 5.12). This interesting phenomenon occurs in 14 out of 16 subjects. Sub1 and Sub3 do not exhibit this phenomenon. The local maxima on the KL(SUP-TOU) curve indicates that the hand transport EM_TVel curves in TOU and SUP are maximally different within a localised region bounded by maximum forearm supination acceleration and velocity.

Figure 5.12: Results of local investigations using KL divergence components. The graphs of all 16 subjects for the 3 main comparisons are arranged starting with Sub1 in the top left corner of each set of comparison. Sub2 is to the right of Sub1 and so and so forth. □, ▣ and ▤ indicate maximum values of 0.02, 0.1 and 0.18 respectively on the vertical axis. All horizontal axes range from 0 to 100. The first and second red lines in KL(SUP-TOU) represent maximum forearm supination acceleration and velocity respectively. The first and second red lines in KL(CYL-SUP) represent initiation of hand aperture closure and maximum hand aperture closing velocity respectively.

5.3.1.4 Discussion for SUP-TOU comparison

Results of global investigations in Section 5.3.1.1 conclude that the hand transport EM_TV_{el} profiles for all 16 subjects are different for SUP and TOU tasks. This result is not unexpected as all the SUP (red) and TOU (blue) plots for all subjects (Appendix B) exhibit visually observable difference in amplitude throughout the entire movement duration.

Results from section 5.3.1.2 provide overwhelming evidence indicating that forearm supination (SUP task) significantly decreases the maximum EM_TV_{el}, average EM_TV_{el} and approach velocity. Significant decrease (Desmurget et al., 1996) and increase (Desmurget et al., 1996; Gosselin-Kessiby et al., 2008; Rand & Stelmach, 2005) in peak wrist transport velocity with forearm supination and pronation respectively have been reported. These results have been interpreted to infer that hand orientation and transport are interdependently controlled and implemented (Desmurget et al., 1996; Gosselin-Kessiby et al., 2008; Rand & Stelmach, 2005). In addition to this argument, the forearm anatomy and biomechanics of forearm supination are also likely to contribute to the observed phenomenon. It is known that the forearm supination-pronation axis extends obliquely from the ulnar styloid process to the lateral epicondyle. Due to the orientation of this axis, forearm supination from a fully pronated position will necessarily rotate the hand laterally away from the torso (Figure 5.13). Hence, in the experiment in this study, forearm supination from a fully pronated starting position essentially turns the hand away from the object which is located along the midline of the torso. Thus, when forearm supination is performed during hand transport towards the object, the resultant hand TV_{el} is reduced. The fact that pronation has been reported in other studies to significantly increase wrist peak transport velocity (Rand & Stelmach, 2005) gives support to this explanation. It should be mentioned that in the study by Rand and Stelmach (2005), subjects performed a reach-to-grasp movement starting from the center of the body and reaching forward horizontal to grasp objects in different orientation. The hand is pronated at the start of the movement. One of object's orientations induces further hand pronation as the hand reaches forward. In this situation, the pronating action rotates the forearm towards the target object in the direction of the hand transport movement. Therefore, it is possible that this pronation increases the resultant hand TV_{el}. Hence, by considering the results in the study by Rand and Stelmach (2005) as well as the current study, changes in hand TV_{el} in the presence of forearm rotation may well be consequences of simple biomechanical principles.

Figure 5.13: Illustration of the forearm supination-pronation axis. Note how the forearm pronates towards medially towards the torso from a supinated position as a result of the oblique axis from ulnar styloid process to lateral epicondyle. Source: Neumann (2010).

Result in this study showing that the relative timings of maximum TVel in SUP and TOU are not statistically different (Section 5.3.1.2 and Table 5.3 SUP-TOU column 4) is in contrary to the results reported by Nagasaki (1989) and Ostry et al. (1987). These authors have shown that with a decrease in velocity, the relative timing of maximum TVel decreased (shifted left). However, a few important differences with this study need to be noted. In those studies, i) forearm is supported by a manipulandum, ii) movement is restricted to horizontal plane, iii) reaching movement is performed without supination, iv) reaching ended at target and v) subjects are required to consciously alter their movement speed to satisfy some predefined criteria. Thus it is possible that all of these conditions especially iii) to v) contributed to the observed discrepancy.

Both normalised jerk and MedianLC indicate that SUP movement decreased in smoothness. This is especially so during the first part of the movement before occurrence of max TVel. MedianLC in particular indicates that all 16 subjects experienced a decrease in spatial smoothness in SUP. Recall that maximum forearm supination velocity occurs during the first part of the movement. Though the possibility that the decrease of smoothness during the first part is, at least partly, due to higher requirement in planning and executing a more complex task in SUP than TOU cannot be ruled out, it is reasonable to suggest that forearm supination also contributes to this observed decrease. Results of assessing movement smoothness in the

second part of the movement appear to be contradictory. While the normalised jerk metric indicates a significant decrease in smoothness temporally, the MedianLC indicates a significant increase in smoothness spatially in SUP (Table 5.4). Osu et al (2011) also reported similar discrepancy in their study when spatial smoothness is preserved whereas temporal smoothness degraded for very slow movement in healthy participants. Temporal smoothness in that study is assessed by mean squared jerk ratio. In this study, it is believed that the cylindrical object in SUP created a smaller but easier target to touch as compared to the (10 × 10) cm square target drawn on the table in TOU. The reduction in target contact area increases accuracy demand which in turn results in more adjustments required. As the normalised jerk metric essentially measures the amount of acceleration changes, that is expected to increase in this case, a decrease in temporal smoothness is recorded. On the other hand, the cylindrical object essentially creates a target that is located vertically off the table surface as compared to the flat square target drawn on the table in TOU. Hence, towards the end, while the hand is required to curve back towards the table in TOU, the hand path in SUP is comparatively straighter as the hand reaches towards a vertical target. In other words, the hand moves directly towards the cylindrical object and does not need to curve back towards the table in SUP. Consequently, 3D curvature is lower for this part of movement resulting in the observed higher MedianLC value that indicates better spatial smoothness in SUP relative to TOU. Further support for this argument is found in the CYL-TOU comparison. Similar decrease in temporal smoothness and increase in spatial smoothness are recorded. However, the increase in spatial smoothness is not statistically significant. This lack of significance may be due to the effect of grasping in CYL. Thus, it is clear that the decrease in both temporal and spatial smoothness during the first part of movement accounts for most, if not all, of the decrease in temporal and spatial smoothness over the entire duration of movement. This provides further support for the hypothesis that forearm supination has a significant effect on the hand transport EM_TVel.

The result of the point-by-point SUP-TOU comparison in section 5.3.1.3 provides a clearer picture on how forearm supination affects the hand transport EM_TVel. The phenomenon that the SUP and TOU EM_TVel curves are locally maximally different within a local region bounded between the occurrence of maximum supination acceleration and maximum supination velocity (Figure 5.12), for 14 out of 16 subjects, clearly suggests that forearm supination affects the EM_TVel amplitude. This result provides further support for the above discussion on how forearm supination may have resulted in decrease of maximum EM_TVel,

average EM_TVel and approach velocity. Acceleration and velocity are directly proportional to the amount of force and momentum respectively. Thus, at maximum supination acceleration and velocity, it is reasonable to believe that forearm supination will exert a significant influence on the EM_TVel amplitude.

5.3.2 CYL-SUP comparison

Recall that the only difference between the SUP and CYL tasks is that the CYL task involves grasping a cylindrical object (Section 3.2). It is believed that the influence of grasping on the hand transport TVel can be determined by comparing the differences between the hand transport TVel profiles from these two tasks.

5.3.2.1 Results for global investigation: ANey, DFD, SDFD and KL divergence

With reference to Table 5.2, ANey indicates that all 16 subjects' SUP EM_TVel and CYL EM_TVel profiles are statistically significantly different. Base on the thresholds that are set in Section 5.3.1.1 for DFD, SDFD and KL divergence measure, all except for 1 subject (Sub6) agree with the results for ANey test. However, it is worth to note that the DFD and KL divergence measure values for this subject are very near to their respective thresholds that indicate existence of differences. Base on visual comparison between the SUP (red) and CYL (magenta) EM_TVel curves for this subject (Figure 5.3), it is more likely to conclude that these two curves are indeed different.

5.3.2.2 Results for post-hoc analyses of specific kinematic parameters

CYL's maximum EM_TVel and approach velocity are statistically significantly higher and lower, respectively, than that of SUP's (Table 5.3). Unlike the SUP-TOU comparison, in this case, there is insufficient evidence to conclude that the average EM_TVels in SUP and CYL are significantly different. These results are well supported by the observations that (i) 11 subjects exhibited higher CYL maximum EM_TVel, (ii) 11 subjects exhibited lower CYL approach velocity and (iii) only 8 subjects exhibited higher CYL average EM_TVel. Of these subjects, only 6 show higher maximum and average EM_TVel in CYL than in SUP. There are 7 subjects with higher maximum EM_TVel and yet lower approach velocities in CYL than in SUP. On the other hand, there are only 4 subjects with both maximum EM_TVel and approach velocities being higher at the same time in CYL.

From Figure 5.9, it is observed that the relative timing of maximum EM_TVel for CYL is the earliest at 44.63% of the entire movement duration. However, this is not significantly different from the relative timing of maximum EM_TVel for TOU (Table 5.3). On an individual level, under the CYL-TOU comparison, only 8 and 7 subjects recorded minimum MaxLag(CYL-TOU) values of -2 (Figure 5.11) and a minimum difference in relative timing of maximum EM_TVel of -2.5% (Figure 5.10) respectively, indicating that CYL EM_TVel is located to the left relative to TOU EM_TVel. Next, CYL-SUP comparison is conducted in order to isolate the effect of grasping. As a group, when comparing the relative timing of maximum EM_TVel, a slight shift to the left (relative to SUP) in CYL's distribution of relative timing of maximum EM_TVel is observed (Figure 5.9). The ANOVA result indicates that this observation is statistically significant with a mean shift of 5.4% time point to the left (Table 5.3). A more detailed analysis at an individual subject level gave a much clearer picture. 12 subjects exhibited a left shift of maximum EM_TVel in CYL relative to SUP of at least 2.5% time point (Figure 5.10). Similarly, 11 subjects recorded minimum MaxLag(CYL-SUP) values of -2 (Figure 5.11), indicating that CYL EM_TVel is located to the left relative to SUP EM_TVel. These corresponded to a decrease in relative timing of max EM_TVel of at least 3.4%.

With reference to Table 5.4, as a group, temporal smoothness of the entire movement and after occurrence of maximum EM_TVel show statistically significant increase in normalised jerk value in CYL (decrease in temporal smoothness). Respectively, 10 and 12 out of 16 subjects exhibited higher normalised jerk values for CYL than for SUP. Temporal smoothness before occurrence of maximum EM_TVel is found to be not significantly different. Results from CUBE-SUP are similar to these. MedianLC value of movement after occurrence of maximum EM_TVel decreases statistically significantly in CYL (decrease in spatial smoothness). 11 out of 16 subjects exhibit lower MedianLC values for CYL than for SUP. However, spatial smoothness for both the entire movement and before occurrence of maximum EM_TVel are not statistically significantly different between SUP and CYL. From CUBE-SUP comparison, the results indicate significant decrease in spatial smoothness for the entire movement and after occurrence of maximum EM_TVel. Similar to CYL-SUP comparison, difference in spatial smoothness before occurrence of maximum EM_TVel is found to lack statistical significance here as well.

5.3.2.3 Results for local investigation

Graphs of this point-by-point comparison (Section 5.2.2) for all 16 subjects for CYL-SUP comparison are shown in Figure 5.12. To facilitate discussion, the curves for this pair of comparison are denoted by $KL(CYL-SUP)$ (Figure 5.12). It should be noted that the summation over all the points on a $KL(CYL-SUP)$ curve is equal to the $KL(v_{CYL}, u_{SUP})$ value (Eq 5.9).

A local maxima on the $KL(CYL-SUP)$ curve is observed to occur between initiation of hand aperture closure and maximum hand aperture closing velocity (Figure 5.12). This phenomenon occurs in 11 out of 16 subjects. Sub3, Sub6, Sub9, Sub14 and Sub15 do not exhibit this phenomenon. The local maxima on the $KL(CYL-SUP)$ curve indicates that the EM_TVel curves in SUP and CYL are maximally different within a localised region bounded by initiation of hand aperture closure and maximum hand aperture closing velocity. It is also interesting to note that 10 out of these 11 subjects exhibit lower EM_TVel in CYL than in SUP within the region bounded by initiation of hand aperture closure and maximum hand aperture closing velocity.

5.3.2.4 Discussion for CYL-SUP comparison

As a group, there is no clear and consistent pattern on how the inclusion of grasping in CYL affects the maximum EM_TVel , average EM_TVel and approach velocity (Section 5.3.2.2). This is especially so with only 50% of the subjects showing higher CYL average EM_TVel . While it appears that maximum EM_TVel increases in CYL, the lower approach velocity suggests that this increase may be occurring in the earlier part of the movement. The 7 subjects with higher maximum EM_TVel and yet lower approach velocities in CYL gives support to this speculation. Nevertheless, the 11 subjects with decrease in approach velocities in CYL are consistent with the expectation that hand transport $TVel$ will decrease to facilitate final adjustments required for successfully grasping the cylindrical object.

The relative timing of maximum EM_TVel for CYL at 44.63% in this study supports observations (Ronnqvist & Rosblad, 2007; Supuk et al., 2011) that high velocity portion of hand transport $TVel$ is accomplished in the earlier part of the entire movement duration. In addition, on both group and individual levels, the results in Section 5.3.2.2 strongly suggest that the additional grasping component in CYL results in a significant temporal ‘shift’ of the hand transport EM_TVel curve. This left ‘shift’, relative to SUP, essentially ensures that the

higher velocities are accomplished in the earlier part (less than 50% time point) of the movement and a lengthening of the deceleration phase. Online adjustments of grasp (Zaal et al., 1998) and orientation (Gosselin-Kessiby et al., 2008) are shown to exist. Therefore, it is possible that grasping in the presence of supination (CYL) resulted in online adjustments that in turn lengthen the deceleration phase.

Evidences tend to support the hypothesis that grasping and hand transport are planned and executed inter-dependently on each other (Paulignan et al., 1991b; Saling et al., 1996; Timmann et al., 1996a; Zaal et al., 1998). Changes in grasping have been shown to affect hand transport kinematics and vice versa. This study not only confirms these prevalent views, but also provides additional information on how and when grasping affects the hand transport TVel. The results in this study very clearly show that both temporal and spatial smoothness decrease significantly after the occurrence of maximum EM_TV_{el} (Table 5.4). The grasping action in CYL is the only difference between SUP and CYL. Hand aperture closure occurs after the occurrence of maximum EM_TV_{el} and maximum aperture closure velocity typically occurs during the last 80-90% of the entire movement duration. Decreases in both temporal and spatial smoothness after the occurrence of maximum EM_TV_{el} are thus closely associated with this hand aperture closure event. Hence, it is concluded that hand aperture closure during grasping, in the presence of forearm supination, has a significant effect on hand transport TV_{el}.

Timmann et al. (1996a, 1996b) noted that as the hand approaches the object, the temporal relationship between the hand transport and grasping components becomes tightly coupled. Results from section 5.3.2.3 reveal that initiation of hand aperture closure and maximum hand aperture closing velocity bound a region in which the SUP and CYL EM_TV_{el} curves are locally maximally different in 11 out of 16 subjects who exhibited significant difference in CYL-SUP EM_TV_{el} curves comparison (Figure 5.12). Recall also that 10 out of these 11 subjects exhibit lower EM_TV_{el} in CYL than in SUP within this region. These results provide further support to the argument that grasping cause a significant decrease in hand transport EM_TV_{el} which is believed to facilitate fine adjustments and positioning as the hand approaches the object.

5.3.3 CUBE-CYL comparison

Recall that the only difference between the CYL and CUBE tasks is that a wooden cube is used in place of the cylindrical object in the CUBE task (Section 3.2). This condition is designed to investigate if the hand transport TVel will be affected by a change of object shape that effectively reduces the number of opposition axis from infinity to 2. The results from this comparison will also be used to determine if it is feasible to construct a common normative hand transport EM_TVel profile for the CYL and CUBE task later in Chapter 6.

5.3.3.1 Results for global investigation: ANey, DFD, SDFD and KL divergence

ANey indicates that 13 subjects' CYL and CUBE EM_TVel curves are statistically significantly different. DFD, SDFD and KL divergence measure agree with ANey's identification of the 3 subjects (Sub5, Sub9 and Sub10) who do not show significant difference between their CYL and CUBE hand transport EM_TVel curves. However, DFD and SDFD also identified a fourth subject (Sub12) who does not show geometric difference between his CYL and CUBE EM_TVel curves. KL divergence measure agrees with DFD and SDFD but in addition identify a fifth subject (Sub16) who does not exhibit substantial difference.

5.3.3.2 Results for post-hoc analyses of specific kinematic parameters

CYL maximum EM_TVel and average EM_TVel are statistically significantly higher than that of CUBE (Table 5.3). On the contrary, the CYL and CUBE approach velocities are not significantly different. Again these results are well supported by the observations that (i) 14 subjects exhibited lower CUBE maximum EM_TVel, (ii) 12 subjects exhibited lower CUBE average EM_TVel and (iii) only 7 subjects exhibited lower CUBE approach velocity. Taking into consideration the CUBE-SUP comparison, it can be inferred that CUBE has the lowest maximum and average EM_TVel while CYL has the lowest approach velocity. Also, it should be noted that the average EM_TVel is the only parameter in CUBE that is significantly lower than that in both SUP and CYL.

The relative timing of maximum EM_TVel for CUBE is not significantly different from the relative timing of maximum EM_TVel for TOU or CYL (Table 5.3). On an individual level, under the CUBE-TOU comparison, only 7 subjects recorded minimum MaxLag(CUBE-TOU) values of -2 (Figure 5.11) and a minimum difference in relative timing of maximum EM_TVel of -2.5% (Figure 5.10) each, indicating that CUBE EM_TVel is located to the left

relative to TOU EM_TV_{el}. CUBE-SUP comparison yields very similar results as the CYL-SUP comparison (Figures 8 and 9). In CUBE-CYL comparison, 6 subjects recorded difference in relative timing of maximum EM_TV_{el} greater than 2.5% (Figure 5.10) and 6 subjects recorded MaxLag(CUBE-CYL) values of at least 2 (Figure 5.11), indicating that the EM_TV_{el} in CUBE is located to the right relative to the EM_TV_{el} in CYL. These corresponded to an increase in relative timing of max EM_TV_{el} between 2.6% and 4.1%. In contrast, 7 subjects recorded difference in relative timing of maximum EM_TV_{el} between -2.5% and 2.5% (Figure 5.10a) and 7 subjects recorded MaxLag(CUBE-CYL) values between -1 and 1 (Figure 5.11a), indicating that the EM_TV_{el} in CUBE is temporally similar to that in CYL.

With reference to Table 5.4, as a group, there is insufficient evidence to conclude that temporal smoothness is significantly different between CYL and CUBE. Spatial smoothness for CUBE-CYL comparison is similar to that of CUBE-SUP comparison in which the results indicate significant decrease in spatial smoothness for the entire movement and after occurrence of maximum EM_TV_{el}. Respectively, 11 and 14 out of 16 subjects exhibit lower MedianLC values for CUBE than for CYL. Also, difference in spatial smoothness before occurrence of maximum EM_TV_{el} is found to lack statistical significance here as well.

5.3.3.3 Results for local investigation

Graphs of this point-by-point comparison (Section 5.2.2) for all 16 subjects for CUBE-CYL comparison are shown in Figure 5.12. To facilitate discussion, the curves for this pair of comparison are denoted by KL(CUBE-CYL) (Figure 5.12). It should be noted that the summation over all the points on a KL(CUBE-CYL) curve is equal to the $KL(v_{CUBE}, u_{CYL})$ value (Eq 5.9).

In this case, there does not seem to be any observable consistent behaviour in the KL(CUBE-CYL) curves across all subjects (Figure 5.12). Recall that 3 subjects namely, CUBE-CYL Sub5, CUBE-CYL Sub9 and CUBE-CYL Sub10 do not show any significant difference between CYL and CUBE EM_TV_{el} curves as assessed by ANey, DFD, SDFD and $KL(v_{CUBE}, u_{CYL})$. Their respective KL(CUBE-CYL) curves are all generally flat (Figure 5.12), agreeing with these assessments.

5.3.3.4 Discussion for CUBE-CYL comparison

Movement time has been noted to be significantly longer for concave than convex objects (Ansuini et al., 2007; Schettino et al., 2003). Clearly, object shape influences the kinematic of reaching to some extent. In the current study, the cube has only 2 opposing faces, in sharp contrast to the cylinder's infinite number, for grasping which inevitably increases the accuracy demand of positioning the hand in preparation of the final grasp. According to Fitt's law, this increase in accuracy demand will result in a decrease in movement speed. As a group, by replacing the cylinder with a cube, the maximum and average EM_TVel decrease significantly while the approach velocity is not significantly different. This seems to suggest that in response to an increase in task demand (cube), subjects decrease the amplitude of EM_TVel in the earlier part of the movement.

The similarity between the results of CYL-SUP and CUBE-SUP comparisons give further support to the hypothesis that grasping induces significant changes in EM_TVel temporally by causing a 'phase shift' to the left relative to SUP. On the other hand, similar to the SUP-TOU comparison, the CUBE-CYL comparison seems to suggest that the CUBE EM_TVel curve has 'shifted' to the right relative to CYL EM_TVel curve. However, closer examination reveals that the maximum increase of 4.1% in relative timing in CUBE maximum EM_TVel is even smaller than the minimum increase of 5.7% recorded in SUP-TOU comparison. Furthermore, almost 50% of the subjects do not show appreciable difference in relative timing of maximum EM_TVel as well as substantial MaxLag(CUBE-CYL) in CUBE-CYL comparison. Therefore, it is concluded that there is insufficient evidence to indicate that CYL and CUBE EM_TVels differ temporally. The results show that by replacing the cylinder with a cube the EM_TVel curves are not affected temporally.

In this study, the cube is oriented so that the two opposing sides, which are parallel to each other, are perpendicular to the hand's approach direction. In comparison to the cylindrical object which offers infinite number of opposing sides, there is strictly only one axis along which the cube can be grasped properly. Cuijpers et al. (2004) study on the effect of small variations in shape on grasping kinematics concluded that appropriate grasping locations are selected prior to or early in the movement. Grip aperture and orientation are then gradually adjusted. Similarly, Santello (2002) noted that gradual shaping of the hand takes place over the entire reach duration. With a drastic change in shape and decrease in number of opposing faces, it is believed that more fine adjustment, either in orientation or finger positioning or

both, is performed just before object contact so as to grasp the cube successfully. As a result, spatial smoothness decreases towards the end of the movement while temporal smoothness is not significantly different as shown in our data.

The only difference between CUBE and CYL is the use of a wooden cube instead of a cylindrical object for grasping. There is no additional movement component and the concurrent lack of any observable consistent behaviour in the KL(CUBE-CYL) curves across all subjects (Figure 5.12) further supports the above arguments (Sections 5.3.1 and 5.3.2) that supination and grasping are responsible for the local maximas observed in the KL(SUP-TOU) and KL(CYL-SUP) curves respectively (Figure 5.12). Additionally, the fact that the conclusions from the KL(CUBE-CYL) curves agree largely with ANey, DFD, SDFD and KL divergence measure (section 5.3.3.3) give confidence to the validity of this method of curve comparison.

5.4 Concluding remarks

In this chapter, a total of 4 global measures, 11 kinematic parameters and 1 point-by-point local measure are used to ensure that an extensive and thorough evaluation is performed to detect differences between a pair of hand transport EM_TV_{el} curves. Hence, two hand transport EM_TV_{el} curves are considered similar only if all the above measures fail to detect a difference. Such strict requirement is imposed so as to minimise the chance of missing important forearm supination and grasping kinematic events that exert significant influence on the hand transport TV_{el} profile. As a result, only 3 pairs of hand transport EM_TV_{el} curves (CUBE-CYL Sub5, Sub9 and Sub10) are considered to be similar. In other words, it can be concluded that forearm supination and grasping exert significant influence on the hand transport EM_TV_{el} profile while the change in object shape may not have as strong an influence.

To this author's knowledge, this is the first study that focuses on identifying feasible landmarks for time normalisation (via landmark registration) of hand transport TV_{el} curves of a reach-to-grasp task. Forearm supination results in decrease in temporal and spatial smoothness during the early part of the movement as well as a general decrease in hand transport TV_{el} amplitude. This decrease is particularly obvious between the occurrences of maximum supination acceleration and maximum supination velocity. These forearm

supination kinematic parameters are thus regarded as events that significantly affect the hand transport TVel profile.

Grasping, in the presence of forearm supination, results in a ‘temporal shifting’ of hand transport TVel so that higher velocities are accomplished in the earlier part of the movement in order to give more time for deceleration and grasp adjustment. Also, decreases in both temporal and spatial smoothness are noted in the later part of the movement. Incidentally relatively large decrease in hand transport TVel is noted between initiation of aperture closure and maximum aperture closing velocity. Hence these grasping kinematic parameters are believed to exert a significant influence on the hand transport TVel profile.

Although, the hand transport EM_TV_{el} profiles of 3 subjects (CUBE-CYL Sub5, Sub9 and Sub10) are not significantly different when the number of opposition faces decreases from infinity (cylinder) to two (cube), as a whole group, significant decrease in hand transport EM_TV_{el} amplitude in the earlier part of the movement and decrease in spatial smoothness towards the end of the movement are detected. These suggest that it may be inappropriate to construct a common normative hand transport EM_TV_{el} for the CYL and CUBE tasks.

The main objective of this chapter is to identify forearm supination and grasping kinematic events that exert significant influence on the hand transport TVel profile. To this end, the results in this chapter identified two time periods, namely, (i) between times of occurrences of maximum forearm supination acceleration and maximum forearm supination velocity and (ii) between times of initiation of hand aperture closure and maximum aperture closing velocity during which significant changes in hand transport TVel amplitude have been observed. These two time periods consist of forearm supination and grasping kinematic parameters that may be considered as landmarks to be used in time normalisation (via landmark registration) of hand transport TVel curves in addition to times of movement onset, maximum TVel and movement offset. Castiello et al. (1993) noted that time of initiation of hand aperture closure (time of maximum aperture) is an important temporal landmark that indicates temporal coupling with wrist maximum deceleration. Also, this parameter plays an important role in determining the hand closure times under different task situations in an influential reach-to-grasp model by Hoff and Arbib (1993). In terms of curve registration, the two identified time periods need to be represented by two time points in order for them to be used as landmarks in time normalisation via landmark registration. One possibility is to use the (i) mean time of

the times of maximum forearm supination acceleration and velocity and (ii) mean time of the times of initiation of hand aperture closure and maximum aperture closing velocity to represent the two time periods.

In conclusion, the investigation in this chapter is successful in identifying additional landmarks that can potentially improve the time normalisation of a set of hand transport TVel curves for a reach-to-grasp task. In turn, this is expected to produce better representative hand transport EM_TV_{el} curves with prediction intervals that accurately define the boundaries of normal hand transport TV_{el} curves. In the next chapter, these potential landmarks will be examined for their relevance and feasibility in time normalisation via landmark registration.

Chapter 6

Construction of Normative Hand Transport Tangential Velocity

From the results in Chapter 5, significant changes in hand transport TVel have been observed in association with two time periods, namely, (i) between times of maximum forearm supination acceleration and velocity and (ii) between times of initiation of hand aperture closure and maximum aperture closing velocity. These have been interpreted to suggest that forearm supination and grasping significantly affect the hand transport TVel during a reach-to-grasp task. Therefore, the first objective of this chapter is to determine if and how these events can be accounted for in the hand transport TVel curve registration (time normalisation) process. The second objective is to investigate how normative hand transport TVel curves, based on the 16 subjects in this study, for both the CYL and CUBE reach-to-grasp tasks can be constructed.

6.1 Supination and grasping events in time normalisation of hand transport TVel

In the context of curve registration, the two aforementioned time intervals cannot be used directly as landmarks in landmark registration. Hence, two kinematic events namely ‘Supination Event’ (SupE) and ‘Aperture Event’ (AperE) are defined to represent these two intervals.

$$\text{SupE} = \frac{(\text{Time of max supination acceleration} + \text{Time of max supination velocity})}{2} \quad (6.1a)$$

$$\text{AperE} = \frac{(\text{Time of aperture closure initiation} + \text{Time of max aperture closing velocity})}{2} \quad (6.1b)$$

Thus, whether both these events are viable kinematic landmarks to be used in the time normalisation of hand transport TVel shall be investigated. Let SupE_TVEl_Amp and AperE_TVEl_Amp denote the amplitude of hand transport TVel when SupE and AperE occurred respectively. Also, let SupE_Time and AperE_Time denote the proportion time (proportion of movement duration) of occurrence of SupE and AperE respectively. In order to analyse the relevance of SupE and AperE in the time normalisation of hand transport TVel curves, the variances of (i) SupE_TVEl_Amp and AperE_TVEl_Amp and (ii) SupE_Time

and AperE_Time will be examined. This is performed on each subject’s set of TVel curves for CYL and CUBE tasks that are subjected to the nonlinear time normalisation (NTN) procedure described in Chapter 4.

6.1.1 SupE and AperE in CYL task

An illustration of the SupE and AperE for a typical subject performing the CYL task is shown in Figure 6.1. For this subject, it is clearly observed that the variances of SupE_TVel_Amp and AperE_TVel_Amp differ greatly while the variances of SupE_Time and AperE_Time distributions are fairly similar. More specifically, the variance of SupE_TVel_Amp distribution is greater than that of AperE_TVel_Amp distribution. Similar plots for other subjects can be found in Appendix D-1.

Figure 6.1: Illustration of SupE and AperE of a typical subject for the CYL task. This is a set of hand transport TVel curves of a typical subject after applying the NTN procedure. The filled triangles on the left of the curves represent the SupE of each trial. The filled circles on the right of the curves represent the AperE of each trial. Note that the horizontal spread of both the SupE and AperE are comparable while the vertical spread of SupE is clearly larger than that of AperE.

The standard deviations (SD) of SupE_TVel_Amp, AperE_TVel_Amp, SupE_Time and AperE_Time for all subjects are collated in Table 6.1. From Table 6.1, it can be clearly observed that only 8 out of 16 the subjects exhibited lower AperE_Time SD (highlighted in yellow) than SupE_Time SD. Furthermore, the group mean of AperE_Time SD is not

significantly lower than the group mean of SupE_Time SD. On the other hand, 14 out of 16 subjects exhibited lower AperE_TVel_Amp SD than SupE_TVel_Amp SD. The group mean of AperE_TVel_Amp SD is also found to be significantly lower than the group mean of SupE_TVel_Amp SD. These results support the observations made earlier in Figure 6.1.

Recall that SupE and AperE are essentially kinematic events of the orientation and grasp components respectively. Hence, SupE_TVel_Amp can be seen as describing the coupling between the orientation and hand transport components during occurrence of SupE. Similarly, AperE_TVel_Amp describes the coupling between the grasp and hand transport components during occurrence of AperE. The above results indicate that the mean variance of AperE_TVel_Amp is significantly lower than that of SupE_TVel_Amp. From a motor control perspective, a lower level of variance is often indicative of a higher degree of control. The uncontrolled manifold (UCM) concept (Scholz and Schoner, 1999) explains and explores how the central nervous system (CNS) manages the problem of redundancy in complex multi-joint human movements. In a nutshell, the UCM concept suggests that the CNS controls only those variables that are crucial to the successful accomplishment of a given task. The controlled variables will exhibit lower degree of variability than those uncontrolled variables that have little or no effect on the outcome of the task. Invoking the principle of UCM, the above results infer that while the CNS seems to control the occurrences of SupE and AperE relative to the movement duration equally, it is not the case relative to the hand transport TVel amplitude. That is, SupE occurs over a significantly larger variability of hand transport TVel amplitude. In other words, this result suggests that the hand transport component has a stronger coupling with the grasp component (aperture closing) than the orientation component (supination).

In order to thoroughly determine the feasibility of using both SupE and AperE as additional time normalisation landmarks, NTN4 and NTN5 are performed. NTN4 refers to the set of NTN TVel curves that are subjected to one additional adjustment using movement onset, maximum TVel, AperE and movement offset times. NTN5 refers to the set of NTN TVel curves that are subjected to one additional adjustment using movement onset, SupE, maximum TVel, AperE and movement offset times. Hence, NTN4 will additionally align the AperE temporally while the NTN5 will additionally align both the SupE and AperE temporally. The performance of LTN, NTN, NTN4 and NTN5 procedures are compared. The results of this comparison for two typical subjects are shown in Figure 6.2 (similar

comparisons for other subjects are presented in Appendix E). The solid curve is the point-by-point hand transport EM_TVel and the dotted curves are the 95% point-by-point prediction interval. The prediction interval defines the interval in which a new observation can be expected. With reference to Figure 6.2a and 6.2b, it is clear that for this subject the NTN (cyan), NTN4 (red in Figure 6.2a) and NTN5 (red in Figure 6.2b) procedures resulted in prediction intervals that are narrower and more regular than the LTN (black) procedure. The NTN4 procedure increases the prediction interval relative to the NTN procedure (Figure 6.2a and 6.2c) in the regions to the right where AperE is being aligned. By visual inspection of the curves in Appendix E, this same effect is observed in 13 out of 16 the subjects. Most of these increases in prediction intervals are modest and more importantly do not cause any irregularity in the shape of the prediction interval bounds. In fact, in some cases, the increase in prediction interval improves the shape of its bounds. For example, the NTN prediction intervals of Sub8, Sub11 and Sub13 exhibit an hour glass shape with a narrow neck (Appendix E). From a clinical movement assessment perspective, an excessively narrow prediction interval will increase the possibility of wrongly assessing a normal movement to be pathological (also known as false negatives). NTN4 removes the hour glass shaped prediction intervals in these three subjects, hence providing support for the use of AperE as an additional landmark. On the contrary, the NTN5 procedure resulted in two typical phenomena illustrated in Figures 6.2b and 6.2d. By visual inspection of all the curves in Appendix E, 12 out of 16 subjects exhibited either a decrease in regularity of the prediction interval bounds (double peaks) (Figure 6.2b) or a large increase in prediction interval in the regions to the left where SupE is being aligned (Figure 6.2d) or both. The increase in prediction interval is so big in some cases that the resulting lower prediction bound extends into the negative hand transport TVel amplitude as illustrated in Figure 6.2d. Recall that by definition, hand transport TVel cannot be negative. Hence, this type of prediction interval is deemed to be undesirable. These results, together with those in Table 6.1, provide support to the use of AperE as the only additional landmark required for the final adjustment. Hence, NTN4 is chosen in favour over NTN5 for this CYL task.

Table 6.1: The 1st and 2nd columns contain the standard deviations (SD) of the amplitude of transport TVel during the occurrences of SupE and AperE respectively for each subject for CYL task. The 3rd and 4th columns contain the SD of the proportion time that SupE and AperE occur. Highlighted cells indicate lower SD value.

Sub	Standard deviation (SD) of			
	SupE_TV _{el} _Amp	AperE_TV _{el} _Amp	SupE_Time	AperE_Time
1	0.085921117	0.032974245	4.910021808	3.338341823
2	0.081896277	0.036073726	3.011090611	3.854770974
3	0.104319234	0.03510866	3.421473316	4.01174858
4	0.08244669	0.062637817	4.882957859	5.397572932
5	0.10066145	0.036072227	4.094598507	2.953947189
6	0.03949279	0.038876608	1.62283778	3.432772824
7	0.094865369	0.028610641	4.101333041	3.281608893
8	0.082671792	0.033678773	3.080262051	4.039646793
9	0.089226292	0.069259348	4.48285868	2.501028595
10	0.105736485	0.031576379	2.996254682	2.805240945
11	0.051445853	0.080453418	2.2183528	4.985816395
12	0.041658196	0.03173775	4.281121206	3.469992425
13	0.119874764	0.069344503	5.138353117	7.186345544
14	0.136522296	0.041648932	9.540643328	3.892494721
15	0.101334798	0.039396276	4.99297398	2.814421489
16	0.021869277	0.074567342	1.851851852	3.928371007
Mean	0.083746417	0.04637604	4.039186539	3.86838257
<i>p</i> -value (1 tailed)		0.000946109		0.37541616

(a)

(b)

(c)

(d)

Figure 6.2: EM_TVels (solid curves) and 95% prediction intervals (dotted curves) resulting from LTN, NTN, NTN4 and NTN5 procedures for CYL task. Black: LTN; Cyan: NTN; Red: NTN4 or NTN5. (a) Plot of LTN, NTN and NTN4 for Sub10. (b) Plot of LTN, NTN and NTN5 for Sub10. Note in (b) that NTN5 resulted in double peak in the prediction interval upper bound (red dotted). (c) Plot of LTN, NTN and NTN4 for Sub12. (d) Plot of LTN, NTN and NTN5 for Sub12. Note in (d) that NTN5 resulted in prominent negative region in the prediction interval lower bound (red dotted).

6.1.2 SupE and AperE in CUBE task

Similar analysis of SupE and AperE for the CUBE task is conducted (refer to Appendix D-2 for plots). For the CUBE task, the result in Table 6.2 suggests that the CNS exercises higher amount of control over the occurrence of AperE relative to the movement duration as well as relative to the hand transport TVel amplitude. In Chapter 5 it is concluded that the CUBE task is comparatively more complex than the CYL task. It is observed that the spatial smoothness decreased in response to an increased in task demand of grasping a cube with a drastically reduced number of opposition faces for grasping as compared to the cylinder. It is thus conceivable that the CNS increases the amount of control over AperE in response to a more difficult grasping task. Graphical analysis of the effect of NTN4 and NTN5 procedures for the CUBE task (Appendix E) results in the same observations as that for the CYL task in section 6.1.1. Hence, the NTN4 procedure is also selected over the NTN5 procedure for the CUBE task.

Table 6.2: The 1st and 2nd columns contain the standard deviations (SD) of the amplitude of transport TVel during the occurrences of SupE and AperE respectively for each subject for CUBE task. The 3rd and 4th columns contain the SD of the proportion time that SupE and AperE occur. Highlighted cells indicate lower SD value.

Sub	Standard deviation (SD) of			
	SupE_TV _{el} _Amp	AperE_TV _{el} _Amp	SupE_Time	AperE_Time
1	0.104863496	0.033105416	7.109383564	2.867810333
2	0.124638657	0.032810783	5.675064638	4.065548749
3	0.14454126	0.017416171	6.820917825	1.925820404
4	0.140027121	0.057539776	6.864620592	2.52713449
5	0.145335342	0.033827996	5.351458462	1.603465256
6	0.035741911	0.026885958	1.774657125	1.459379012
7	0.066759955	0.046794546	3.238535405	3.061628832
8	0.057892374	0.021969199	2.417120817	1.478711913
9	0.07372246	0.046143776	3.628873693	2.456759104
10	0.166936394	0.032739668	5.272287404	3.656432456
11	0.0333537	0.134289857	1.789968487	4.58839408
12	0.098038879	0.030405889	6.511528238	3.084008935
13	0.115840531	0.048867249	4.948924842	3.213125182
14	0.148542455	0.033411948	9.643864123	3.961405024
15	0.070971968	0.04047453	1.946506843	2.160246899
16	0.095535945	0.05679691	3.563324648	4.517807546
Mean	0.101421403	0.043342479	4.784814794	2.914229888
p-value (1 tailed)		0.0006		0.003

6.2 Constructing normative hand transport EM_TVel curve

Up to this point, normative hand transport EM_TVel curves have been successfully constructed at the individual level for all the 16 subjects in this study via the NTN4 procedure. However, the ultimate aim of this study is to construct a representative normative hand transport EM_TVel curve, with appropriate prediction bounds, for a reach-to-grasp task, against which performance of stroke patients with upper extremity movement disorder can be assessed. Therefore, it is essential that a normative hand transport EM_TVel curve be as representative of the normal general population as possible. In order to accomplish this, it shall be investigated if it is possible to construct such a normative benchmark for the entire group of 16 subjects for the CYL and CUBE task each. In the event where a normative curve is non-existence, it is also important to explore other possible alternatives to represent the general population.

(a)

Figure 6.3: Consolidation of EM_TVel curves for all 16 subjects for (a) CYL task and (b) CUBE task subjected to NTN4 procedure.

6.2.1 Normative hand transport EM_TVel curve for CYL and CUBE tasks

The hand transport EM_TVel curves of 16 subjects for the CYL and CUBE tasks subjected to the NTN4 procedure are shown in Figure 6.3a and 6.3b respectively. Expectedly, there is a considerable amount of inter-subject variability that is likely to adversely affect the quality of the group hand transport EM_TVel curve calculated from these sets of curves. In order to verify this, group EM_TVel curves for LTN, NTN and NTN4 TVel curves will be constructed. 16 sets of NTN4 hand transport TVel curves from all 16 subjects (159 trials for CYL and 160 trials for CUBE) are combined into a single collection of NTN4 hand transport TVel curves. Group hand transport EM_TVel curve and its prediction intervals are constructed. This is repeated for the LTN and NTN hand transport TVel curves. The result is shown in Figure 6.4 with black, cyan and red representing LTN, NTN and NTN4 respectively for both the CYL and CUBE tasks. It can be clearly seen that the prediction intervals are so large that there is essentially no difference between the LTN, NTN and NTN4 methods. In fact, the prediction intervals are generally big (widest at ± 0.3 mm/msec) and even contain negative values at the end of the movement (approximately last 20%). Note that hand transport TVel by definition cannot be negative. Clearly, it is not feasible to combine all 16 subjects into a single big group for both CYL and CUBE tasks.

(a)

(b)

Figure 6.4: Group hand transport EM_TVel (solid curves) with 95% prediction intervals (dotted curves) for LTN, NTN and NTN4 TVel curves for (a) CYL and (b) CUBE. These are obtained by considering all 16 subjects as 1 big group. Black: LTN; Cyan: NTN; Red: NTN4.

6.2.2 Subject groupings via *k*-means

An alternative strategy is to investigate if the 16 sets of hand transport TVel curves (each belonging to a subject) can be divided into smaller groups. As there is no a priori knowledge on how the group might be divided, unsupervised learning cluster analysis method such as *k*-means algorithm (Martinez et al, 2011) shall be used to discover possible groupings among

these 16 sets of hand transport TVel curves. This algorithm is implemented in MATLAB via the ‘kmeans’ function. In order to use this algorithm, a feature space needs to be defined.

Recall that the main motivation justifying the need to perform time normalisation is to ensure that all important kinematic events related to the movement under investigation have been temporally aligned. In NTN4, each subject’s set of hand transport TVel curves are aligned according to the times of (i) movement onset, (ii) maximum TVel, (iii) AperE and (iv) movement offset. Hence, it makes good sense to ensure that subjects are grouped according to these 4 features. As the proportion times of movement onset and offset are 0 and 1, respectively, for all subjects, only the proportion times of maximum TVel and AperE provide useful information for classification (grouping) purposes. In addition, based on visual inspection of all the hand transport EM_TVel curves from all 16 subjects (Figure 6.3), the amplitude of maximum TVel seems a likely discriminating feature. By grouping curves with similar proportion times of maximum TVel and AperE as well as maximum TVel amplitude, much of the inter-subject variability observed in Figure 6.3 can be reduced. Consequently, the k -means feature space is three dimensional consisting of (i) proportion times of maximum TVel, (ii) proportion times of AperE and (iii) maximum TVel amplitude. Therefore, each of the 16 hand transport EM_TVel curve is characterised by these features and is represented as a point in this three dimensional feature space. In a nutshell, the k -means algorithm seeks to identify k clusters (groupings) among these 16 data points within the feature space by optimizing a pre-specified distance measure. In this study, the squared Euclidean distance is used. The silhouette statistic (Kaufman & Rousseeuw, 1990) and the gap statistic method (Tibshirani et al., 2001) are used to determine the optimal number of clusters, k . The silhouette statistic is implemented using the ‘silhouette’ function in Matlab that implements the algorithm described by Kaufman and Rousseeuw (1990). The following is a summary of the silhouette statistic (Martinez et al, 2011).

Given observation i , denote the average dissimilarity to the rest of the points in its own cluster as a_i . For any other cluster, c , the average dissimilarity of i to all the points in that cluster is denoted as $d(i,c)$. Finally the minimum of these average dissimilarities is denoted by b_i . Then the silhouette width for observation i is defined as

$$sw_i = \frac{(b_i - a_i)}{\max(a_i, b_i)} \quad (6.2)$$

The average silhouette width is then

$$sw = \frac{1}{n} \sum_i^n sw_i \quad (6.3)$$

where n is the total number of observations in the feature space. In this study, $n = 16$. To use the silhouette statistic to determine the optimal number of clusters, k -means is performed with a range of number of clusters. In this study, k -means is performed with 2 to 9 clusters. The value of sw is computed for each run of k -means and the number of clusters with the highest sw is selected as the optimal number of clusters. In general, $sw > 0.5$ indicates reasonable clustering while $sw < 0.2$ indicates data do not exhibit cluster structure (Kaufman & Rousseeuw, 1990). In addition, the silhouette plot of Eq 6.2 for each run of k -means is also consulted to sieve out clustering that contains negative sw_i . Note that Eq 6.2 ranges from -1 to 1 with -1 indicating bad clustering. Hence, clustering with negative sw_i should be avoided.

The gap statistic method (Tibshirani et al., 2001) is implemented with the Matlab codes provided by Martinez et al. (2011) but with the agglomerative clustering method replaced by the k -means method. The strategy for this method is to compare the within cluster dispersion with the dispersion of a reference null distribution which assumes no clustering. The number of clusters that results in the greatest difference or gap between the observed dispersion (based on data) and the expected dispersion (based on reference null distribution) is recorded as the optimal number of clusters. For ease of referencing, the procedure outlined by Martinez et al (2011) is reproduced here with minor modifications.

Assume k clusters $C_1, \dots, C_k$ obtained from k -means, where the r^{th} cluster has n_r observations. Define the sum of pairwise distances for all points in cluster r as

$$D_r = \sum_{i,j \in C_r} d_{ij} \quad (6.4)$$

$$W_k = \sum_{r=1}^k \frac{1}{2n_r} D_r \quad (6.5)$$

where $d_{i,j}$ is the squared Euclidean distance between observations i and j . The within cluster dispersion index is then defined as $\ln(W_k)$ for $k = 2, \dots, K$. Next, a random sample of n observations is generated based on the uniform distribution. This is repeated B number of times thus generating B number of random samples each with n observations based on the uniform distribution. In this study, $B = 1000$. Then, k -means is applied on each of these samples for $k = 2, \dots, K$ and the within cluster dispersion index for each sample is calculated using Eq 6.5 as $\ln(W_{k,b}^*)$ where $b = 1, \dots, 1000$. The average of these values is

$$\overline{W_k} = \frac{1}{B} \sum_b \ln(W_{k,b}^*) \quad (6.6)$$

Finally, the estimated gap statistic is defined as

$$gap(k) = \overline{W_k} - \ln(W_k) \quad (6.7)$$

and the optimal number of cluster, k , corresponds to the maximum $gap(k)$ value.

6.2.2.1 Subject groupings via k -means for CYL task

The 16 hand transport EM_TVel curves for CYL task in Figure 6.3a are represented by points in the 3D feature space described in section 6.2.2. The 3D coordinates of these points are given in Table 6.3. Note that the values in the three columns are of different scales. In order to remove the effect of scales, each of these columns is standardized to have 0 mean and 1 standard deviation. These standardized coordinates are then used in the k -means algorithm. Note that, in this study, the k -means algorithm is repeated 10 times with randomly selected starting values for each k . The best clustering is then automatically selected from these 10 replicates by the ‘kmeans’ algorithm for each k . For the CYL task, $k = 2, 3, \dots, 7$. That is, the search for the optimal number of clusters is limited between 2 and 7.

Table 6.3: Values of parameters representing the 16 EM_TV_{el} curves for the CYL task. Each row gives the 3D coordinates of the point that represent the corresponding EM_TV_{el} curve in the feature space defined by max EM_TV_{el} time, AperE and max EM_TV_{el} amplitude. Note that the standardised coordinates are used in the *k*-means algorithm.

Sub	Max EM_TV _{el} (%Time)	AperE (%Time)	Max EM_TV _{el} (Amplitude)	Standardized		
				Max EM_TV _{el}	AperE	Max EM_TV _{el}
1	44.32835821	77.8358209	0.575759101	-0.0449	-0.16292	-0.86753
2	38.93333333	77.4	0.563995939	-0.88829	-0.2192	-0.99124
3	41.53846154	89.42307692	0.558799672	-0.48104	1.333451	-1.04589
4	49.23076923	83.84615385	0.676396663	0.721471	0.613249	0.190887
5	47.96296296	79.81481481	0.675919367	0.52328	0.092644	0.185867
6	44.35294118	76.17647059	0.50863138	-0.04106	-0.37721	-1.57352
7	48.49056604	83.86792453	0.70300822	0.605758	0.616061	0.470763
8	36.10169492	73.30508475	0.771521867	-1.33095	-0.74802	1.191329
9	55.77777778	87.55555556	0.727525447	1.74494	1.09228	0.728614
10	39.3258427	75.61797753	0.657548434	-0.82693	-0.44933	-0.00734
11	36.29032258	60.48387097	0.81914466	-1.30146	-2.40375	1.692182
12	42.77777778	80.92592593	0.630487068	-0.2873	0.236132	-0.29195
13	38.15217391	66.19565217	0.493345628	-1.0104	-1.66613	-1.73428
14	55.68181818	87.72727273	0.70256446	1.729939	1.114455	0.466096
15	42.64150943	82.35849057	0.743339034	-0.3086	0.421133	0.894927
16	52.26337449	83.02469136	0.723957364	1.195547	0.507166	0.691088

The results of the silhouette statistic (Figure 6.5a) and the gap statistic method (Figure 6.5c) both indicate a clear maximum point when $k = 3$ clusters. Corresponding silhouette values for individual observations (subjects) reveal no negative values (Figure 6.5b) confirming that no observation is considered badly clustered when 3 clusters (groups) are formed. Silhouette value plots for other number of clusters are found in Appendix F. Hence, it is determined that the optimal number of clusters for the CYL task is 3.

The 3D plot of the result for this clustering is shown in Figure 6.6 and the subjects in each group are tabulated in Table 6.4. All the sets of individual TV_{el} curves (trials) for each subject in a group are consolidated. The total number of hand transport TV_{el} curves (trials) for each group is shown in Table 6.4. These are then used to calculate the hand transport EM_TV_{el} with 95% prediction interval plots for each of these groups (Figure 6.7). As the sets of individual hand transport TV_{el} curves within a group are selected based on their similarity in mean times of max TV_{el}, mean AperE and mean max TV_{el} amplitude, the adverse effects of undesirable temporal variations on the group hand transport EM_TV_{el} and prediction intervals are expected to be minimal.

(a)

(b)

(c)

Figure 6.5: Determination of the optimal number of clusters via the silhouette statistic and gap statistic method for CYL task. (a) Silhouette statistic showing a clear maximum at $k = 3$. (b) Silhouette values of individual observations that are all positive. (c) Gap statistic showing a clear maximum at $k = 3$.

Figure 6.6: Graphical results of clustering subjects into $k = 3$ groups via k -means algorithm for the CYL task.

Table 6.4: Clustering result for CYL task showing subjects in each cluster.

Cluster	Subjects	Total number of trials
A	1, 2, 3, 6, 10, 12, 13	70
B	8, 11	20
C	4, 5, 7, 9, 14, 15, 16	69

A comparison between Figure 6.4a and Figure 6.7 clearly reveals that the prediction intervals after grouping (Figure 6.7) improved tremendously especially for the NTN (cyan) and NTN4 (red). The widest NTN4 prediction interval among the 3 groups is ± 0.2 mm/msec in Group A (Figure 6.7a). This is a reduction from ± 0.3 mm/msec in the whole big group (Figure 6.4a). For Group A (Figure 6.7a), although the width of the prediction intervals for LTN (black), NTN (cyan) and NTN4 (red) are similar, the prediction interval for LTN exhibits a double peak which is a strong indication of misalignment of the max TVel in individual hand transport TVel curves. For Group B (Figure 6.7b), the LTN prediction interval is general wider and dips slightly into the negative hand transport TVel region at about 10% movement duration. The NTN4 procedure which additionally aligns the AperE adjusts the suspiciously

narrow NTN prediction interval between 40% and 60% movement duration. For Group C (Figure 6.7c), the LTN prediction interval is again generally wider, dips slightly into the negative hand transport TVel region at about 15% movement duration and exhibit double peak near max hand transport EM_TV_{el}. All in all, these results further illustrate the inadequacy of the LTN method as well as provide strong evidence for the need for grouping subjects for the purpose of obtaining appropriate 95% prediction intervals for the CYL task.

The need for grouping subjects in this CYL task is further justified by the clearly different characteristics of the hand transport EM_TV_{el} curves in the 3 groups. The hand transport EM_TV_{el} curve in Group A (Figure 6.7a) has maximum amplitude of about 0.57 mm/msec occurring at about 40% movement duration. The hand transport EM_TV_{el} curve in Group B (Figure 6.7b) has maximum amplitude of about 0.8 mm/msec and is clearly skewed to the right with this maximum value occurring at about 35% movement duration. Finally, the hand transport EM_TV_{el} curve in Group C (Figure 6.7c) has maximum amplitude of about 0.7 mm/msec and is visually symmetrical. This result demonstrates that there are possibly 3 different sets of control strategies (in terms of controlling max TV_{el}, time of max TV_{el} and A_{perE}) for this CYL task that need to be properly differentiated and represented so as to provide a more accurate normative hand transport TV_{el} curve for movement disorder assessment purposes. For instance, subjects in Grp A may be considered as deploying a conservative strategy that favours accuracy over speed. Subjects in this group move the slowest (among the three groups) during the 30-70% of the entire movement, reach a modest peak velocity before 50% of movement duration and spend the rest of the time gradually slowing down, presumably to facilitate grasping. On the other hand, subjects in Grp B are characterized by an impulsive strategy in which movement accelerates quickly and peaks at the highest value at the earliest time. This early peak time is presumably necessary, in response to a high peak velocity, to give sufficient amount of time to slow down to perform the grasp. Lastly, subjects in Grp C seem to use a well-balanced strategy which spends half the time accelerating to a peak velocity value that is between those of the other two groups and the other half of the time decelerating. In addition, the acceleration and deceleration appear to be similar. Hence, it is possible that this strategy is the most efficient one with respect to energy expenditure. All these information is clearly lost when all the subjects are considered as one whole big group (Figure 6.4a).

(a)

(b)

(c)

Figure 6.7: EM_TV_{el} curves (solid curve) with 95% prediction intervals (dotted curves) for (a) Grp A, (b) Grp B and (c) Grp C, identified via *k*-means algorithm for the CYL task. Black: LTN; Cyan: NTN; Red: NTN4.

6.2.2.2 Subject groupings via *k*-means for CUBE task

The clustering procedure described in section 6.2.2.1 is repeated here for the CUBE task. The standardized 3D coordinates of the points representing the 16 CUBE hand transport EM_TVel curves (Figure 6.3b) are given in Table 6.5. Determination of the optimal number of clusters for the CUBE task is not as straightforward as that for the CYL task. The silhouette statistic (Figure 6.8a) increases with the number of clusters thus is not helpful in determining the optimal number of clusters. However, the gap statistic method plot (Figure 6.8d) contains a maximum value at $k = 6$ clusters. Unfortunately, the silhouette value plot in Figure 6.8b shows that an observation is likely to be badly clustered (negative value) which suggests that $k = 6$ clusters may not be preferred. From Figure 6.8d, it can be observed that the gap statistic value when $k = 7$ clusters is fairly close to the maximum. A check with the silhouette value plot for $k = 7$ clusters (Figure 6.8c) reveals no negative value in this case. Hence, it is concluded that the optimal number of clusters for the CUBE task is $k = 7$. Silhouette value plots for other number of clusters are found in Appendix F.

Table 6.5: Values of parameters representing the 16 EM_TVel curves for the CUBE task. Each row gives the 3D coordinates of the point that represent the corresponding EM_TVel curve in the feature space defined by max EM_TVel time, AperE and max EM_TVel amplitude. Note that the standardized coordinates are used in the *k*-means algorithm.

Sub	Max EM_TVel (%Time)	AperE (%Time)	Max EM_TVel (Amplitude)	Standardized		
				Max EM_TVel	AperE	Max EM_TVel
1	48.10344828	82.93103448	0.580052603	0.453159508	0.495546696	-0.52044489
2	35.85365854	73.59756098	0.504185931	-1.34880717	-0.70706081	-1.29088109
3	42.59259259	91.2345679	0.503924915	-0.35749753	1.565447582	-1.29353173
4	43.03571429	75.625	0.646710109	-0.29231351	-0.44582758	0.156470998
5	47.73584906	80.18867925	0.689386128	0.399084984	0.142197327	0.589851686
6	48.69047619	80.17857143	0.490705791	0.539512397	0.140894946	-1.4277737
7	49.62962963	80.92592593	0.646958609	0.677663601	0.237190727	0.158994555
8	38.7755102	73.57142857	0.760915455	-0.9189974	-0.71042794	1.316241562
9	55.33333333	88.88888889	0.724686896	1.516688942	1.263209496	0.948335702
10	38.42105263	78.28947368	0.629114026	-0.97113876	-0.10251316	-0.02221957
11	40	65.18867925	0.801700231	-0.73887269	-1.7905357	1.73041641
12	42	83.2	0.613229227	-0.444669	0.530202599	-0.18353184
13	34.71910112	62.69662921	0.4823567	-1.51570266	-2.11163353	-1.51255985
14	58	88.22222222	0.630681332	1.90896053	1.17731025	-0.00630337
15	45.4	81	0.718347048	0.055477277	0.246735088	0.883953695
16	52.0754717	79.62264151	0.677877637	1.037451483	0.069264005	0.472981412

Figure 6.8: Determination of the optimal number of clusters via the silhouette statistic and gap statistic method for CUBE task. (a) Silhouette statistic does not contain maximum value. (b) Silhouette values of individual observations for $k = 6$ that contain 1 negative observation. (c) Silhouette values of individual observations for $k = 7$ that are all positive. (d) Gap statistic showing a maximum at $k = 6$ and a close to maximum value at $k = 7$.

The results of clustering the CUBE task into 7 groups of subjects are shown in Figure 6.9 and Table 6.6. This result seems to suggest that the current group of 16 subjects use a greater variety of control strategies (in terms of controlling max TVel, time of max TVel and AperE) for the CUBE task than for the CYL task. Recall that the CUBE task is deemed to be more demanding as a higher level of accuracy in hand orientation and fingers placement is required. It would seem that this group of subjects utilise a greater variety of control strategies in response to this increase in demand for accuracy. However, this can only be confirmed with a bigger sample size of subjects.

Figure 6.9: Graphical results of clustering subjects into $k = 7$ groups via k -means algorithm for the CUBE task.

Table 6.6: Clustering result for CUBE task showing subjects in each cluster.

Cluster	Subjects	Total number of trials
A	9, 14	20
B	3	10
C	2, 13	20
D	8, 11	20
E	4, 10, 12	30
F	5, 7, 15, 16	40
G	1, 6	20

The hand transport EM_TV_{el} curves and their 95% prediction intervals for these 7 groups are shown in Figure 6.10. Again, a comparison between Figure 6.4b and Figure 6.10 clearly reveals that the prediction intervals after grouping (Figure 6.10) improved tremendously especially for the NTN (cyan) and NTN4 (red). The widest NTN4 prediction interval among the 7 groups is ± 0.2 mm/msec in Group D (Figure 6.10d). This is a reduction from ± 0.3 mm/msec in the whole big group (Figure 6.4b). In groups E and F which have more than 2 subjects, the LTN procedure again resulted in double peaks (Figures 6.10e and 6.10f) in the prediction intervals indicating serious misalignment of max TV_{el} temporally. The hand transport EM_TV_{el} curves among these 7 groups (Figure 6.10) are also visibly different in terms of the max EM_TV_{el} values and skewness.

(a)

(b)

(c)

(d)

(e)

(f)

Figure 6.10: EM_TVvel curves (solid curve) with 95% prediction intervals (dotted curves) for (a) Grp A, (b) Grp B, (c) Grp C, (d) Grp D, (e) Grp E, (f) Grp F and (g) Grp G identified via *k*-means algorithm for the CUBE task. Black: LTN; Cyan: NTN; Red: NTN4.

6.3 Concluding remarks

Analyses in this chapter suggest that the hand transport component of both the CYL and CUBE tasks couples stronger with the grasp component than with the orientation component. Final adjustment to the time normalisation of hand transport TVel curves involving the use of SupE also resulted in erroneous prediction intervals. Hence, in the context of constructing a normative hand transport TVel curve, only AperE is used in the final adjustment to the time normalisation of hand transport TVel curves.

The NTN4 method of time normalisation aligns important kinematic events of the CYL and CUBE tasks in this study and as a result provides a good mean of identifying potential groupings among the subjects. Though single representative normative hand transport EM_TVvel curves for the CYL and CUBE tasks do not seem possible for the entire group of subjects, normative hand transport EM_TVvel curves for different groups of subjects have been demonstrated to exist. This is also a significant and novel contribution of this study towards the development of an objective norm-referenced upper extremity (UE) movement quality assessment system.

Chapter 7

Normative Hand Transport Tangential Velocity for the Detection of Deviation from Normal Movement - A Pilot Patient Trial

Previous chapters have focused on reducing intra (Chapter 4, 5 and 6) and inter (Chapter 6) subject variability that eventually resulted in the establishment of 3 and 7 groups of normative hand transport EM_TV_{el} profiles for the CYL and CUBE tasks respectively (Chapter 6). It is noted in Chapter 6 that the LTN and NTN4 procedures resulted in visibly different 95% prediction intervals in most of these groups. Although, it has been argued that the NTN4 95% prediction interval, which aligns key kinematic events of the reach-to-grasp tasks, is theoretically sound and more accurate, an important question that remains to be answered is what difference does it make practically? More precisely, do the seemingly narrow gaps between the LTN and NTN4 95% prediction intervals make a difference in assessing patient's performance? Then, the next logical question is how can an established normative hand transport EM_TV_{el} profiles be used to provide an objective measure of patient's performance? In order to answer these questions, a pilot trial involving 3 stroke patients will be conducted in this chapter.

7.1 Patient trial

This pilot patient trial is conducted as part of another project by Singapore Polytechnic and National University Hospital under the ethics approval by NHG Domain Specific Review Board (DSRB) (ref: 2012/00192).

7.1.1 Patient and method

Three male hemiplegic stroke patients who are 35, 67 and 63 years old and 1, 5 and 5 years post-stroke respectively are recruited for this study. All patients are affected on their dominant side and have recovered functional grasping action to be able to perform reach-to-grasp task without the assistance of the non-affected side. The experimental protocol described in Chapter 3 is implemented with the exceptions that only CYL and CUBE tasks as well as only 3 trials (instead of 10) are conducted for each patient.

All patient trials are conducted in the presence of a qualified physiotherapist who is familiar with and capable of conducting observational upper extremity movement assessment of stroke

patients. Based on the therapist's assessment, Patient 1 and 3 are assessed to be 'highly recovered' with 'normal' reach-to-grasp movements. Patient 2, however, exhibited clear signs of tremor and large degree of compensatory shoulder and trunk movements during the tasks.

7.1.2 Data processing

The same data processing procedure described in section 3.3 is applied to the sets of patient data. It should be noted that as each patient trial will be analysed individually, there is no need to calculate an ensemble mean curve for the set of hand transport TVel profiles of each patient. Hence, it is sufficient to time normalise each trial by its Phase 1 total movement duration. That is, each TVel profile is linearly time normalised by setting movement onset as 0% and movement offset as 100%.

7.1.3 Results of patient trial for CYL task

The hand transport TVel profiles of the 3 patients performing the CYL task are presented in Figure 7.1. The hand transport TVel profiles for Patient 1 and 3 in Figure 7.1a and 7.1c respectively appear similar to the normative EM_TV_{el} curves for CYL obtained in Chapter 6. At this point, it would have seemed that both these patients may have regained normal reach-to-grasp movement which concurs with the physiotherapist's observational assessment. However, closer examination reveals that Patient 1 exhibited some submovements in the first 20% and last 90% of the movement and Patient 3 exhibited strong second peaks in all his 3 trials in the last 80% of the movement indicating presence of corrective submovements. There are also clear signs of existence of inflection points again indicating presence of corrective submovements. These results clearly demonstrate the added value of kinematic analyses in detecting such subtle deviations from normality which would have been otherwise missed by observational assessment. Finally, the highly irregular hand transport TVel profiles for Patient 2 in Figure 7.1b clearly reflect the tremor and compensatory movements observed by the physiotherapist.

(a)

(b)

(c)

Figure 7.1: Hand transport TVel curves of CYL task Phase 1 for (a) Patient 1, (b) Patient 2 and (c) Patient 3. Blue: 1st trial. Magenta: 2nd trial. Green: 3rd trial. All individual trials are time normalised to their respective total movement duration. Patient 1 and 3 are assessed to be ‘highly recovered’ via observational assessment by a qualified physiotherapist.

7.1.4 Results of patient trial for CUBE task

The hand transport TVel profiles of the 3 patients performing the CUBE task are presented in Figure 7.2. Again, the overall shape of the hand transport TVel profiles for Patient 1 and 3 in Figure 7.2a and 7.2c respectively appear similar to the normative EM_TVel curves for CUBE obtained in Chapter 6 suggesting that their reach-to-grasp movements may be ‘normal’ which concurs with the physiotherapist’s observational assessment. However, similar to the CYL task, presence of secondary peaks and signs of inflection points indicate existence of corrective submovements which would have been otherwise missed by observational assessment. Furthermore, closer examination reveals that Patient 1 seems to exhibit an increased amount of submovements (more secondary peaks) in the last 70% of the movement for the CUBE task (Figure 7.2a) as compared to the CYL task (Figure 7.1a). This result further supports the conclusion in Chapter 5 that an increase in accuracy demand of the CUBE task resulted in a decrease in spatial smoothness of the hand transport movement when the grasping becomes eminent. Lastly, in Figure 7.2b, the highly irregular hand transport TVel profiles for Patient 2, clearly reflect the tremor and compensatory movements observed by the physiotherapist.

(a)

(b)

(c)

Figure 7.2: Hand transport TVel curves of CUBE task Phase 1 for (a) Patient 1, (b) Patient 2 and (c) Patient 3. Blue: 1st trial. Magenta: 2nd trial. Green: 3rd trial. All individual trials are time normalised to their respective total movement duration. Patient 1 and 3 are assessed to be ‘highly recovered’ via observational assessment by a qualified physiotherapist.

7.2 Performance of LTN and NTN4 95% prediction intervals

In section 6.2.2, normal subjects are divided into groups, based on similarities of their individual hand transport EM_TVel profiles, so as to reduce inter-subject temporal variability when constructing more generalized grouped hand transport EM_TVel profiles. As a result of this grouping, differences between the 95% prediction interval associated with the LTN EM_TVel curve and the 95% prediction interval associated with the NTN4 EM_TVel curve become clearly observable for both the CYL (Figure 6.7) and CUBE (Figure 6.10) tasks. Recall that the NTN4 procedure (Chapter 4, 5 and 6) is proposed to reduce erroneous intra-subject temporal variability so as to improve the validity and accuracy of the 95% prediction interval. The focus of this section is to examine if the results of using NTN4 95% prediction interval in assessing patients' hand transport TVel profile differ from that when LTN 95% prediction interval is used.

Patient 1 and 3 are regarded as 'highly recovered' who exhibited 'near to normal' hand transport TVel profiles for both the CYL (Figure 7.1a and 7.1c) and CUBE (Figure 7.2a and 7.2c) tasks. The hand transport TVel profiles from these 2 patients are deemed to be useful towards the purpose of this section. On the other hand, the hand transport TVel profiles for Patient 2 for both CYL (Figure 7.1b) and CUBE (Figure 7.2b) tasks are highly irregular and clearly deviates from normative TVel profiles greatly. Hence, Patient 2 will be excluded from the following analyses.

The hand transport TVel profiles of Patient 1 and 3 will be compared with the 3 and 7 groups of normative hand transport EM_TVel profiles for CYL obtained in section 6.2.2.1 and for CUBE obtained in section 6.2.2.2 respectively. Theoretically, each patient's hand transport TVel profile should be compared with the normative hand transport EM_TVel profile from the group that the patient belongs to. However, there is not enough information in this current study to determine the grouping of each patient. Possible solutions to determine patients' grouping will be discussed in the next chapter as 'future work'. Therefore, for now, the patients' hand transport TVel profiles will be compared with all the 3 and 7 groups of CYL and CUBE, respectively, normative hand transport EM_TVel profiles.

7.2.1 Comparison with grouped hand transport EM_TVel profiles for CYL

The results for Patient 1 and 3 for the CYL task are shown in Figure 7.3 and Figure 7.4 respectively. In addition, the percentage of movement duration that a patient's hand transport

TVel falls outside a 95% prediction interval for the CYL task is tabulated in Table 7.1. With respect to Grp B (Figures 7.3b and 7.4b) and Grp C (Figures 7.3c and 7.4c), the hand transport TVel profiles of both patients contain large portion that clearly fall outside the 95% prediction intervals of LTN (black) and NTN4 (red). Referring to Table 7.1, when NTN4 95% prediction interval is used in Grp B, the portion of patient's TVel profile falling outside increases by more than 10% (green highlight) for trials 2 and 3 of Patient 3 and by more than 20% (yellow highlight) for all trials of Patient 1 and trial 1 of Patient 3. In other words, if both patients belong to Grp B, their extent of deviation from normal movement velocity amplitude would have been underestimated by the LTN 95% prediction interval by as much as 30.43% (Grp B Patient 3 trial 1). This underestimation is significant especially in the context of using the normative 95% prediction to monitor the progress of recovery.

In contrast to Grp B and C, the hand transport TVel curves for all trials of both patients appear to be most similar to the normative hand transport EM_TVel profiles in Grp A (Figures 7.3a and 7.4a). If both patients belong to Grp A and LTN 95% prediction interval is used, it would seem reasonable to conclude that both patients have regained 'normal' reach-to-grasp movement velocity amplitude. In fact, with the exception of Patient 1 trial 1, the portion of patients' TVel profiles of the remaining 5 trials falling outside the LTN 95% prediction interval is at most 14.17% (Table 7.1 Grp A). In fact, trial 3 of both patients appears to fall completely within the LTN 95% prediction interval (green curve on Figures 7.3a and 7.4a). However, when NTN4 95% prediction interval is used, 26.05% of Patient 1 trial 3 and 29.93% of Patient 3 trial 3 (Table 7.1) are detected to fall outside this prediction interval. Both of these increments are more than 20% as compared to LTN 95% prediction interval. These effects are clearly seen in the interval between 15% and 40% where the green curve is observed to be located within the gap between the red and black dashed curves (Figure 7.3a and 7.4a). In other words, under the assumption that both patients have not recovered 'normal' reach-to-grasp movement velocity amplitude fully, the NTN4 95% prediction interval is indeed more accurate and sensitive in detecting deviation from normal movement velocity amplitude over the entire movement duration, especially for patients with high level of functional recovery.

Table 7.1: Percentage amount of movement duration of the CYL task that a patient's hand transport TVel falls outside the 95% prediction intervals associated with LTN and NTN4 EM_TV_{el} curves. Groups A, B and C are obtained in section 6.2.2.1. Cells highlighted in green and yellow indicate absolute difference between LTN and NTN4 that exceed 10% and 20% respectively.

		Patient 1		Patient 3	
		LTN (%)	NTN4 (%)	LTN (%)	NTN4 (%)
Grp A	Trial 1	30.23256	33.33333	11.30435	20.86957
	Trial 2	14.17323	25.19685	2.564103	7.692308
	Trial 3	0.840336	26.05042	7.29927	29.92701
Grp B	Trial 1	41.86047	71.31783	45.21739	75.65217
	Trial 2	34.64567	62.99213	31.62393	50.42735
	Trial 3	31.09244	52.94118	35.76642	50.36496
Grp C	Trial 1	85.27132	73.64341	55.65217	53.91304
	Trial 2	74.80315	76.37795	58.97436	53.84615
	Trial 3	67.22689	68.06723	63.50365	64.23358

(a)

(b)

(c)

Figure 7.3: Comparison of 3 trials of Patient 1 with the 3 groups of CYL EM_TVEl profiles obtained in section 6.2.2.1 for (a) Grp A, (b) Grp B and (c) Grp C. Black solid: LTN EM_TVEl. Black dotted: LTN 95% prediction intervals. Red solid: NTN4 EM_TVEl. Red dotted: NTN4 95% prediction intervals. Blue, magenta and green: patient trial 1, 2 and 3 respectively.

(a)

(b)

Figure 7.4: Comparison of 3 trials of Patient 3 with the 3 groups of CYL EM_TV_{el} profiles obtained in section 6.2.2.1 for (a) Grp A, (b) Grp B and (c) Grp C. Black solid: LTN EM_TV_{el}. Black dotted: LTN 95% prediction intervals. Red solid: NTN4 EM_TV_{el}. Red dotted: NTN4 95% prediction intervals. Blue, magenta and green: patient trial 1, 2 and 3 respectively.

7.2.2 Comparison with grouped hand transport EM_TV_{el} profiles for CUBE

The results for Patient 1 and 3 for the CUBE task are shown in Figure 7.5 and Figure 7.6 respectively. In addition, the percentage of movement duration that a patient's hand transport TV_{el} falls outside a 95% prediction interval for the CUBE task is tabulated in Table 7.2. Once again, from Table 7.2, it can be observed that for Patient 1 Grp C all 3 trials, Grp E trial 1 and 3 as well as Patient 3 Grp F trial 1 and 2, the percentage amount of movement duration that the patients' hand transport TV_{el} profiles falling outside the prediction interval increases by at least 10% when NTN4 95% prediction interval is used. Again, under the assumptions that Patient 1 has not recovered 'normal' reach-to-grasp movement velocity amplitude fully for the CUBE task and also that he belongs to either Grp C or E, then the LTN 95% prediction interval underestimated his deviation from normal movement velocity amplitude by as much as 22.91% (Patient 1 Grp E trial 3). This is clearly observable in Figure 7.10e in the interval between 17% and 37% of movement duration where the green curve falls within the gap between the red (NTN4) and black (LTN) dashed curves. Similarly, if Patient 3 is assumed to

belong to Grp F, then the LTN 95% prediction interval underestimated his deviation from normal movement velocity amplitude by 16.89% (Patient 3 Grp F trial 2). All these results provide more evidence that the NTN4 95% prediction interval is indeed more accurate and sensitive in detecting deviation from normal movement velocity amplitude.

Table 7.2: Percentage amount of movement duration of the CUBE task that a patient's hand transport TVel falls outside the 95% prediction intervals associated with LTN and NTN4 EM_TV_{el} curves. Groups A, B, C, D, E, F and G are obtained in section 6.2.2.2. Cells highlighted in green and yellow indicate absolute difference between LTN and NTN4 that exceed 10% and 20% respectively.

		Patient 1		Patient 3	
		LTN (%)	NTN4 (%)	LTN (%)	NTN4 (%)
Grp A	Trial 1	57.6	57.6	49.42529	49.42529
	Trial 2	67.79661	58.47458	75.32468	67.53247
	Trial 3	53.125	54.16667	78.57143	75
Grp B	Trial 1	56.8	55.2	28.73563	33.33333
	Trial 2	57.62712	61.86441	23.37662	23.37662
	Trial 3	25	33.33333	47.61905	44.04762
Grp C	Trial 1	28.8	43.2	41.37931	47.12644
	Trial 2	10.16949	22.0339	31.16883	40.25974
	Trial 3	0	10.41667	16.66667	19.04762
Grp D	Trial 1	87.2	87.2	33.33333	41.37931
	Trial 2	58.47458	67.79661	28.57143	27.27273
	Trial 3	69.79167	63.54167	35.71429	30.95238
Grp E	Trial 1	54.4	69.6	18.3908	24.13793
	Trial 2	54.23729	51.69492	6.493506	15.58442
	Trial 3	10.41667	33.33333	13.09524	20.2381
Grp F	Trial 1	64	62.4	31.03448	44.82759
	Trial 2	55.9322	61.01695	27.27273	44.15584
	Trial 3	52.08333	58.33333	50	58.33333
Grp G	Trial 1	55.2	53.6	0	0
	Trial 2	49.15254	50	10.38961	10.38961
	Trial 3	41.66667	41.66667	35.71429	39.28571

Compare with EM TVel of LTN & NTN4 (Grp A)
Patient 1; Condition CUBE

(a)

Compare with EM TVel of LTN & NTN4 (Grp B)
Patient 1; Condition CUBE

(b)

Compare with EM TVel of LTN & NTN4 (Grp C)
Patient 1; Condition CUBE

(c)

Compare with EM TVel of LTN & NTN4 (Grp D)
Patient 1; Condition CUBE

(d)

Compare with EM TVel of LTN & NTN4 (Grp E)
Patient 1; Condition CUBE

(e)

Compare with EM TVel of LTN & NTN4 (Grp F)
Patient 1; Condition CUBE

(f)

(g)

Figure 7.5: Comparison of 3 trials of Patient 1 with the 7 groups of CUBE EM_TV_{el} profiles obtained in section 6.2.2.2 for (a) Grp A, (b) Grp B, (c) Grp C, (d) Grp D, (e) Grp E, (f) Grp F and (g) Grp G. Black solid: LTN EM_TV_{el}. Black dotted: LTN 95% prediction intervals. Red solid: NTN4 EM_TV_{el}. Red dotted: NTN4 95% prediction intervals. Blue, magenta and green: patient trial 1, 2 and 3 respectively.

Compare with EM TVel of LTN & NTN4 (Grp A)
Patient 3; Condition CUBE

(a)

Compare with EM TVel of LTN & NTN4 (Grp B)
Patient 3; Condition CUBE

(b)

Compare with EM TVel of LTN & NTN4 (Grp C)
Patient 3; Condition CUBE

(c)

Compare with EM TVel of LTN & NTN4 (Grp D)
Patient 3; Condition CUBE

(d)

Compare with EM TVel of LTN & NTN4 (Grp E)
Patient 3; Condition CUBE

(e)

Compare with EM TVel of LTN & NTN4 (Grp F)
Patient 3; Condition CUBE

(f)

Figure 7.6: Comparison of 3 trials of Patient 3 with the 7 groups of CUBE EM_TVEl profiles obtained in section 6.2.2.2 for (a) Grp A, (b) Grp B, (c) Grp C, (d) Grp D, (e) Grp E, (f) Grp F and (g) Grp G. Black solid: LTN EM_TVEl. Black dotted: LTN 95% prediction intervals. Red solid: NTN4 EM_TVEl. Red dotted: NTN4 95% prediction intervals. Blue, magenta and green: patient trial 1, 2 and 3 respectively.

7.3 An objective measure of deviation from normal movement

In the previous sections, it has been shown that the NTN4 95% prediction interval is more accurate and sensitive in detecting deviation from normal movement velocity amplitude. Hence, from here on, only the NTN4 95% prediction interval will be used.

Up to this point, the above discussions have been focused on detection of deviation from normal movement in terms of the percentage of movement duration that a hand transport TVel profile falls outside a 95% prediction interval. This essentially only assesses whether the amplitude of the hand transport TVel profile over the entire movement duration is within normal range. However, the shape of the hand transport TVel profile is as important as the amplitude in determining if any given hand transport TVel profile can be considered normal. Figure 7.7 illustrates 2 hypothetical cases of extreme situations using the NTN4 EM_TVEl profile from Grp A for the CYL task. Figure 7.7a illustrates the case when a TVel profile

falls almost completely within the 95% prediction interval but has little resemblance (except for the global trend) with the EM_TV_{el} profile. On the other hand, Figure 7.7b illustrates the case when a TV_{el} profile resembles the shape of the EM_TV_{el} to a large extent, albeit being flatter, but falls almost completely outside the 95% prediction interval. Clearly both cases have fallen short of being normal and the strategy to address this issue is to provide an objective measure of deviation from normal movement by accounting for both amplitude and shape of a TV_{el} profile.

Figure 7.7: Two cases of abnormal TV_{el} profiles. (a) A hypothetical extreme case when the TV_{el} profile is well within the 95% prediction interval but has little resemblance with the EM_TV_{el} profile. (b) A hypothetical case when the TV_{el} profile resembles the EM_TV_{el} profile but falls largely outside the 95% prediction interval.

7.3.1 CORT-PIN plot

The proportion of movement duration that a TV_{el} profile falls within a 95% prediction interval (*PIN*) will be used to assess the amount of amplitude deviation from normal range. Hence, *PIN* ranges from 0 to 1, with 0 indicating that the entire TV_{el} profile has fallen outside the 95% prediction interval and 1 indicating that the entire TV_{el} profile falls within the 95% prediction interval.

The degree of which a TV_{el} profile resembles a normative EM_TV_{el} profile will be assessed using the temporal correlation (*CORT*) defined in Eq 4.14. That is, *CORT* between a patient's TV_{el} profile and a normative EM_TV_{el} profile will be computed. As noted before, the main advantage of *CORT* is that it is global trend free and provides a measure of temporal correlation between two time series at a local level. This property is especially important as it is expected for patients' TV_{el} profiles to contain irregularities (sometime subtle) that distort

the shape of the TVel profiles but still exhibit high global correlation with normative EM_TV_{el} profile (Figure 7.7a). Furthermore, *CORT* is relatively easy and cost less to compute as compared to other possible similarity measures such as Frechet distance. *CORT* ranges from -1 to 1 with 1 indicating good positive temporal correlation, 0 indicating no correlation and -1 indicating good negative temporal correlation.

Figure 7.8: Illustration of areas defined on the *CORT*-*PIN* plot. The *CORT* and *PIN* thresholds are represented by the 2 black dashed lines. The minimum *CORT* threshold is represented by the red dashed line. The yellow highlighted area is the ‘normal area’. A hand transport TVel profile with its (*CORT*, *PIN*) position within this ‘normal area’ is considered normal. The grey area is the ‘low recovery area’. A hand transport TVel profile with its (*CORT*, *PIN*) position within this ‘low recovery area’ is considered to have little control and coordination and therefore the *PIN* value is meaningless.

CORT and *PIN* are selected not only for their ease of computation but also for their potential relevance in clinical assessment. A high *CORT* and high *PIN* will indicate recovery to normal movement (Figure 7.8). A high *CORT* and low *PIN* may indicate recovery of control and coordination but perhaps still lacking in speed. In this case, slow movement can indicate either a lack of strength or a lack of ability to control movement in normal speed range. Interpretation of a low *CORT* and high *PIN* case may not be as straightforward because recovery to normal movement velocity likely requires a minimum level of control and coordination. In other words, there may be a minimum *CORT* threshold (red dashed line in Figure 7.8) that is prerequisite for recovery to normal movement velocity. That is, if a stroke patient crosses above this minimum *CORT* threshold with a high *PIN*, it is likely that this

patient has regained sufficient control to generate normal speed but still exhibit corrective submovements that can contribute to the low *CORT* value. Conversely, if a patient falls below this minimum *CORT* threshold, which can be considered ‘low recovery’ (Figure 7.8), then there is no sense in measuring the *PIN*. Finally, a low *CORT* (above minimum *CORT* threshold) and low *PIN* may indicate a case of moderate to high recovery of control, coordination and speed. It is expected that most stroke patients who have recovered moderate to high functional ability be found in this category.

7.3.2 Thresholds for *CORT* and *PIN*

From the above discussions, it is clear that there is a need to define normal levels for *CORT* and *PIN*. Normal subjects hand transport TVel profiles are required to define normal levels for *CORT* and *PIN*. To illustrate the procedure, let’s consider Grp A for CYL task. There are 7 normal subjects in this group (Table 6.4) and so there is a total of 70 hand transport TVel profiles. From Figure 7.9, it can be clearly observed that not all hand transport TVel profile falls completely within the NTN4 95% prediction interval. That is, *PIN* values are not all 1 for all the TVel profiles. Similarly, the temporal correlations (*CORT*) between each TVel profile and the EM_TVel profile are also expected to be different.

Next, the *CORT* and *PIN* values for each of the 70 hand transport TVel profiles are calculated. Hence, each hand transport TVel profile can be represented by an ordered pair (*CORT*, *PIN*) on a Cartesian plane defined by *CORT* as the horizontal axis and *PIN* as the vertical axis where *CORT* = [-1, 1] and *PIN* = [0, 1]. These are represented by the black filled circle markers on Figure 7.10a. Not surprisingly, most of these are clustered around the top right corner near (1, 1). The mean *CORT* and mean *PIN* values are calculated and this is depicted as the black cross on Figure 7.10a. 95% prediction intervals associated with both mean *CORT* and mean *PIN* are constructed based on the *t*-distribution. The vertical dashed line on Figure 7.10a depicts the lower bound of the 95% prediction interval associated with mean *CORT* and this defines the threshold above which *CORT* is considered normal. Similarly, the horizontal dashed line on Figure 7.10a depicts the lower bound of the 95% prediction interval associated with mean *PIN* and this defines the threshold above which *PIN* is considered normal. Hence, in order for a hand transport TVel profile to be considered normal, its (*CORT*, *PIN*) position must fall within an ‘normal area’ defined by these two thresholds (boundaries). This is depicted as the yellow highlighted area in Figure 7.8 and the rectangular

area in the top right corner in Figure 7.10a. This procedure is repeated for Grp B and C of CYL task and the results are shown in Figure 7.10b and 7.10c respectively.

Figure 7.9: A collection of hand transport TVel profiles of all 7 subjects in Grp A of the CYL task. Notice that not all TVel profiles fall completely within the 95% prediction interval and clearly there is variability in terms of temporal correlation between each TVel profile and the EM_TVel profile.

(a)

(b)

(c)

Figure 7.10: *CORT-PIN* plots for (a) Grp A, (b) Grp B and (c) Grp C for the CYL task. The black filled markers represent the normal subjects in each group. The black cross within a circle is the position of the centroid of these black markers calculated as (mean *CORT*, mean *PIN*). The blue, green and red filled markers represent Patient 1, 2 and 3 respectively. P1T1 denotes Patient 1 Trial 1 and so on. The vertical and horizontal black dashed lines define the thresholds above which *CORT* and *PIN*, respectively, are considered normal. A TVel profile with a (*CORT*, *PIN*) position within the top right rectangular area is considered normal.

From the CYL *CORT-PIN* plots in Figure 7.10, unsurprisingly, Patient 2 (green filled markers) TVel profiles are farthest from the ‘normal area’ in all 3 groups indicating accurately that his reach-to-grasp movement is worst among the 3 patients (Figure 7.1). On the other hand, these results suggest that Patient 3 has the best performance. In fact, in Grp A, his trial 2 falls within the ‘normal area’ and trial 1 just falls short of the *PIN* threshold. However, Patient 1 has the best performance consistency among the 3 patients. In order to provide a quantitative analysis for these plots, the performance of each patient TVel profile can be quantified in terms of its shortest distances from both the *CORT* and *PIN* boundaries as shown in Table 7.3. For a given TVel profile, its ordered pair (*dCORT*, *dPIN*) gives a quick assessment of how much improvement is required in *CORT* and *PIN*. Negative *dCORT* value indicates that the corresponding TVel profile is within normal range in terms of temporal

correlation with the normative EM_TVel profile. Negative $dPIN$ value indicates that the corresponding TVel profile is within normal range in terms of the proportion of movement duration that the TVel profile falls within the NTN4 95% prediction interval. From Table 7.3, only Patient 3 has negative distances (highlighted in red) that indicate exceeding the respective $CORT$ and PIN thresholds. Trial with both negative values indicates that its TVel profile is within the ‘normal area’. If such detail is not required, the shortest distance from a $(CORT, PIN)$ position to the ‘normal area’ can be calculated as

$$DisNor = \sqrt{(dCORT)^2 + (dPIN)^2} \quad (7.1)$$

In this way $DisNor$ can be viewed as a measure of deviation from normality. Note that all negative $dCORT$ and $dPIN$ values are set to 0 before calculation. This is done because when either the $CORT$ or PIN value enters the normal range, it no longer contributes towards deviation from normality. The results for the CYL task are shown in Table 7.4. Expectedly, most of the $DisNor$ values for Patient 3 are among the smallest in each group. The mean $DisNor$ values are smallest for Patient 3 in all 3 groups again suggesting that Patient 3 is more highly recovered than the other two patients.

Table 7.3: Distances from each $(CORT, PIN)$ position, representing a TVel profile, to the $CORT$ and PIN boundaries (thresholds) are shown here as $dCORT$ and $dPIN$ respectively for CYL task.

CYL		Patient 1		Patient 2		Patient 3	
		$dCORT$	$dPIN$	$dCORT$	$dPIN$	$dCORT$	$dPIN$
Grp A	Trial 1	0.2086	0.1614	0.6156	0.2567	-0.0555	0.0368
	Trial 2	0.1278	0.0801	0.7818	0.1714	-0.0109	-0.095
	Trial 3	0.1255	0.0886	0.6244	0.2857	0.1418	0.1274
Grp B	Trial 1	0.3704	0.5073	0.5991	0.457	-0.0226	0.5506
	Trial 2	0.3012	0.424	0.8275	0.3812	0.0566	0.2984
	Trial 3	0.3041	0.3235	0.6803	0.4664	0.3108	0.2977
Grp C	Trial 1	0.1688	0.5393	0.6765	0.3115	0.1055	0.342
	Trial 2	0.1504	0.5667	0.7478	0.3601	0.0514	0.3414
	Trial 3	0.1403	0.4836	0.6087	0.4357	0.1044	0.4452

Table 7.4: Shortest distance of each patient marker (shown in Figure 7.10), to the ‘normal area’ as calculated by Eq 7.1 for the CYL task.

<i>DisNor</i>		Patient 1	Patient 2	Patient 3
Grp A	Trial 1	0.2637	0.6670	0.0368
	Trial 2	0.1508	0.8004	0.0000
	Trial 3	0.1536	0.6867	0.1906
	Mean	0.1894	0.7180	0.0758
Grp B	Trial 1	0.6281	0.7535	0.5506
	Trial 2	0.5201	0.9111	0.3037
	Trial 3	0.4440	0.8248	0.4304
	Mean	0.5307	0.8298	0.4282
Grp C	Trial 1	0.5651	0.7448	0.3579
	Trial 2	0.5863	0.8300	0.3452
	Trial 3	0.5035	0.7486	0.4573
	Mean	0.5517	0.7744	0.3868

Similarly, the *CORT-PIN* plots for all 7 groups of the CUBE task are shown in Figure 7.11.

Like the CYL task, Patient 2 is assessed to perform the worst with his CUBE TVel profiles (green filled markers) being farthest from the ‘normal area’ in all the *CORT-PIN* plots. From Figure 7.11, Table 7.5 and 7.6, the TVel profiles of Patient 3 are assessed to be nearest to the ‘normal area’ in all groups except for Grp C. The best performance of Patient 3 is found in Grp E where trial 2 TVel profile is located well within the ‘normal area’ while TVel profiles for trial 1 and 3 are both located very near to the boundaries of the ‘normal area’.

Furthermore, with respect to the EM_TVel profile of Grp E, Patient 3 consistency is high. By taking into consideration the *CORT-PIN* plots for Patient 3 in CYL Grp A (Figure 7.10a) and CUBE Grp E (Figure 7.11e), with 2 out of 6 trials falling within the ‘normal area’, these results suggest that there is a good chance that this patient has attained a high level of recovery for both reach-to-grasp tasks. However, more attention is warranted in identifying factors for causing him to ‘fail’ in the other 4 trials (3 of these are actually very near to the ‘normal area’) so that a more targeted therapy can be designed to help him improve further. For Patient 1, his performances in CYL Grp A (Figure 7.10a) and CUBE Grp C (Figure 7.11c) are rather similar. From these results, this patient clearly has not regained normal reach-to-grasp movement for both tasks. Recall that this patient is only 1 year post-stroke and thus is conceivable that he should continue to require therapy to help him improve his performance further.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Figure 7.11: *CORT-PIN* plots for (a) Grp A, (b) Grp B, (c) Grp C, (d) Grp D, (e) Grp E, (f) Grp F and (g) Grp G for the CUBE task. The black filled markers represent the normal subjects in each group. The black cross within a circle is the position of the centroid of these black markers calculated as (mean *CORT*, mean *PIN*). The blue, green and red filled markers represent Patient 1, 2 and 3 respectively. P1T1 denotes Patient 1 Trial 1 and so on. The vertical and horizontal black dashed lines define the thresholds above which *CORT* and *PIN*, respectively, are considered normal. A TVel profile with a (*CORT*, *PIN*) position within the top right rectangular area is considered normal.

Table 7.5: Distances from each (*CORT*, *PIN*) position, representing a TVel profile, to the *CORT* and *PIN* boundaries (thresholds) are shown here as *dCORT* and *dPIN* respectively for CUBE task.

CUBE		Patient 1		Patient 2		Patient 3	
		<i>dCORT</i>	<i>dPIN</i>	<i>dCORT</i>	<i>dPIN</i>	<i>dCORT</i>	<i>dPIN</i>
Grp A	Trial 1	0.5164	0.3701	0.7431	0.393	-0.0299	0.2884
	Trial 2	0.5691	0.3788	0.7419	0.4982	0.1426	0.4694
	Trial 3	0.2577	0.3358	0.6763	0.4281	0.3586	0.5441
Grp B	Trial 1	0.1183	0.5188	0.7544	0.6843	0.0977	0.3001
	Trial 2	0.1583	0.5854	0.7936	0.6709	0.0576	0.2006
	Trial 3	-0.005	0.3001	0.6603	0.3459	0.19	0.4073
Grp C	Trial 1	0.0501	0.336	0.6881	0.6102	0.2449	0.3753
	Trial 2	-0.0009	0.1243	0.7802	0.5367	0.0734	0.3066
	Trial 3	0.0329	0.0082	0.5302	0.27	0.1585	0.0945
Grp D	Trial 1	0.0783	0.6535	0.7099	0.4877	0.0868	0.1953
	Trial 2	0.0759	0.4595	0.7578	0.4652	-0.0199	0.0542
	Trial 3	-0.0107	0.4169	0.5666	0.3697	0.0722	0.091
Grp E	Trial 1	0.0656	0.4675	0.6863	0.3195	0.0279	0.0129
	Trial 2	0.0516	0.2884	0.7187	0.3531	-0.0681	-0.0727
	Trial 3	-0.0376	0.1048	0.5249	0.1702	0.0229	-0.0261
Grp F	Trial 1	0.3047	0.4133	0.7648	0.5577	-0.0622	0.2376
	Trial 2	0.3372	0.3995	0.7628	0.5291	0.0018	0.2309
	Trial 3	0.0844	0.3726	0.6483	0.3906	0.1446	0.3726
Grp G	Trial 1	0.2963	0.5046	0.7878	0.4827	-0.0281	-0.0314
	Trial 2	0.3352	0.4686	0.8052	0.5706	0.0254	0.0725
	Trial 3	0.0807	0.3853	0.6895	0.3608	0.1641	0.3615

Table 7.6: Shortest distance of each patient marker (shown in Figure 7.11), to the ‘normal area’ as calculated by Eq 7.1 for the CUBE task.

<i>DisNor</i>		Patient 1	Patient 2	Patient 3
Grp A	Trial 1	0.6353	0.8406	0.2884
	Trial 2	0.6836	0.8937	0.4906
	Trial 3	0.4233	0.8004	0.6516
	Mean	0.5808	0.8449	0.4769
Grp B	Trial 1	0.5321	1.0185	0.3156
	Trial 2	0.6064	1.0392	0.2087
	Trial 3	0.3001	0.7454	0.4494
	Mean	0.4795	0.9344	0.3246
Grp C	Trial 1	0.3397	0.9197	0.4481
	Trial 2	0.1243	0.9470	0.3153
	Trial 3	0.0339	0.5950	0.1845
	Mean	0.1660	0.8206	0.3160
Grp D	Trial 1	0.6582	0.8613	0.2137
	Trial 2	0.4657	0.8892	0.0542
	Trial 3	0.4169	0.6765	0.1162
	Mean	0.5136	0.8090	0.1280
Grp E	Trial 1	0.4721	0.7570	0.0000
	Trial 2	0.2930	0.8008	0.0996
	Trial 3	0.1048	0.5518	0.0347
	Mean	0.2900	0.7032	0.0448
Grp F	Trial 1	0.5135	0.9465	0.2376
	Trial 2	0.5228	0.9283	0.2309
	Trial 3	0.3820	0.7569	0.3997
	Mean	0.4728	0.8773	0.2894
Grp G	Trial 1	0.5852	0.9239	0.0000
	Trial 2	0.5761	0.9869	0.0768
	Trial 3	0.3937	0.7782	0.3970
	Mean	0.5183	0.8963	0.1579

7.3.3 Minimum CORT threshold

Finally, the minimum *CORT* threshold that is prerequisite for recovery to normal movement velocity shall be determined. To accomplish this, the *CORT-PIN* plots of groups with at least 3 subjects are considered. Results from such groups will be based on at least 30 TVel profiles and therefore have a higher probability of being more generalizable. CYL Grp A and C and CUBE Grp E and F satisfy this criterion.

As discussed above, Patient 2 has the lowest performance level among the 3 patients and his TVel plots in Figures 7.1b and 7.2b confirm this conclusion. Patient 1 is considered a case of moderate to high recovery with TVel profiles that bear good resemblance with that of a normal subject (Figures 7.1a and 7.2a). Hence, the minimum *CORT* threshold should be determined as the value that separates these two patients on all the *CORT-PIN* plots of the 4 selected groups. For CYL Grp A (Figure 7.10a), the interval that contains all possible *CORT* values that satisfy this is (0.2715, 0.6785). All such intervals for the 4 groups are shown in Table 7.7. The intersections of the CYL and CUBE intervals are (0.321, 0.5497) and (0.3547, 0.5618) respectively, hence the CYL and CUBE minimum *CORT* threshold values can be any value within these respective intervals. More patient trials will be required in order to verify and refine this.

Table 7.7: Determination of minimum *CORT* threshold values for CYL and CUBE tasks.
Intervals containing possible values of minimum *CORT* threshold are shown here for the 4 selected groups. An intersection of these intervals will give the final interval that contains the minimum *CORT* threshold value.

Group	Lower bound	Upper bound
CYL Grp A	0.2715	0.6785
CYL Grp C	0.321	0.5497
CYL interval	0.321	0.5497
CUBE Grp E	0.3547	0.814
CUBE Grp F	0.2507	0.5618
CUBE interval	0.3547	0.5618

7.3.4 Discussion on *CORT-PIN* plot

The *CORT-PIN* plot proposed in this chapter is a novel way of using normative hand transport EM_TV_{el} profile to provide an objective measure of deviation from normal reach-to-grasp movement. It provides an objective mean, which goes beyond subjective visual comparisons, of evaluating the performance of a patient's hand transport TV_{el} profile against a corresponding normative profile. The shortest distance from a patient's hand transport TV_{el} profile to a 'normal area' on the *CORT-PIN* plot (*DisNor*) serves as a measure of the degree of deviation from normal movement on a continuous scale. That is, it is not ordinal and therefore does not suffer from ceiling effect. Furthermore, the 'normal area' defined on a *CORT-PIN* plot is empirically defined. That is, it is model-free and thus is not restricted by assumptions of any underlying motor control principles which provide, at best, a good estimate to model a physical phenomenon. Lastly, the *CORT-PIN* plot provides a means of objectively tracking a patient's progress continuously with reference to the 'normal area'.

That is, it tracks performance improvement relative to both the individual and to an empirically defined norm. Many studies have proposed kinematic parameters to monitor the recovery progress of stroke patients relative to the patients' pre-treatment performance. The amount of increase in post-treatment score is a measure of the amount of improvement achieved. A relative assessment is important and useful in providing information regarding the rate of improvement which is interpreted as a patient's responsiveness to a prescribed therapy. It can also be a source of motivation to a patient to witness improvement no matter how small the amount. However, as guaranteed by the law of diminishing returns, as a patient recovers, the rate of improvement will decline. At this stage, a relative score may no longer be as useful to a therapist as it does not indicate the actual extent of recovery achieved. This is an important piece of information that will help therapist in planning and designing the next stage of appropriate treatment if necessary. A criterion referenced measurement like *CORT-PIN* plot provides both relative and absolute assessment.

However, the *CORT-PIN* plot is not without shortcomings. Firstly, its accuracy is entirely dependent on the accuracy of the normative profiles that are used to define the *CORT* and *PIN* thresholds that in turn define the 'normal area'. The focus of this entire study has been on improving the accuracy of normative profile. Much has been achieved, but it is believed that further improvements can be made with the availability of more healthy and patient subjects in the future. Secondly, the *CORT-PIN* plot only monitors temporal correlation (*CORT*) and amplitude deviation (*PIN*), therefore, may miss other aspects such as smoothness. Other parameters like normalised jerk score can be added to increase the dimension of the *CORT-PIN* plot to become a *CORT-PIN-JERK* plot for instance. However, visualisation becomes difficult if not impossible with higher dimension. Hence, it is not recommended that *CORT-PIN* plot be used in isolation at this stage. To the very least, the time series plot of patient's hand transport TVel profile superimposed on the corresponding normative profile (Figures 7.3, 7.4, 7.5, 7.6) should be consulted in conjunction. For example, in Figure 7.3a, by comparing the hand transport TVel curves of all three trials from Patient 1 with Grp A's EM_TV_{el} curve, it can be observed that all of these three TV_{el} curves exhibit a small 'hump' in the beginning of movement which causes a delay in onset of the acceleration phase. In turn, this causes all three curves to fall outside the 95% prediction interval between 20% and 40% of the entire movement duration. This consistent delay in onset of acceleration phase may be indicative of a need for additional preparation time before the onset of the actual reaching movement. In addition, there are obvious irregularities for a large portion of the

movement, especially after peak TVel during deceleration, which cause the curves' *CORT* values to fall below 'normal' (blue filled markers in Figure 7.10a and Table 7.3). It is believed that these irregularities indicate the existence of corrective submovements as object grasping becomes imminent. On the other hand, unlike Patient 1, Patient 3 exhibits a delay in onset of acceleration phase in only one out of the three TVel curves (Figure 7.4a). Again, due to this delay, the acceleration phase of this TVel curve falls below 'normal' values (green curve in Figure 7.4a). Also, irregularities occurring near the peak TVel and towards the end of movement as compared to the EM_TVel curve are again indicative of corrective submovements. In conclusion, a qualitative evaluation based on the normative EM_TVel profiles is useful in providing additional insights on the nature of the deviations from normal movement, thus further emphasizing the importance of establishing accurate normative EM_TVel profiles for this reach-to-grasp task.

7.4 Concluding remarks

A pilot patient trial with 3 stroke patients is conducted. Hand transport TVel profiles from these patients provide strong indications that the NTN4 95% prediction interval is indeed more accurate and sensitive in detecting deviation from normal movement velocity amplitude in moderate to highly recovered patients than the LTN 95% prediction interval.

Following that, a novel objective measure of deviation from normal movement for reach-to-grasp is proposed in the form of *CORT-PIN* plot based on the NTN4 normative hand transport EM_TVel profiles. Incidentally, the *CORT-PIN* plot categorises the 3 patients into 3 different performance levels. Clearly, *CORT-PIN* plot offers an objective way of monitoring the progress of a patient's recovery by tracking the hand transport TVel profile's position relative to a 'normal area' defined on the plot.

It is important to emphasize that the *CORT-PIN* plot is proposed as an illustration of how normative kinematics can be used to provide an objective assessment of movement performance. It is also proposed with clinical application in mind and it is for this purpose that the plot is kept to be simple and easy to use to maximise the chance of actual eventual clinical implementation. Obviously, more researches, especially with larger sample sizes for both normal subject and patients are needed to verify the results.

Chapter 8

Conclusion and Future Work

8.1 Conclusion

This study has made significant contributions towards the development of a more objective UE assessment for stroke rehabilitation. The criterion referenced assessment approach with thresholds defined by normative data is used in this study. With reference to the stated objectives in Chapter 1, temporal variance inherent in the hand transport TVel profile of a reach-to-grasp task that contributes to an erroneous level of intra- and inter-subject amplitude variance is reduced. Then, by establishing normative hand transport EM_TV_{el} profiles for 2 reach-to-grasp tasks, an objective measure of deviation from normal reach-to-grasp movement is proposed. In the process of achieving these, the following key contributions are made:

- 1) A novel nonlinear time normalisation procedure is proposed in Chapter 4 to reduce temporal variance that resulted in erroneous intra-subject hand transport TV_{el} amplitude variance. The proposed procedure is novel in that it preserves the temporal correspondence between kinematic events of the hand transport, forearm supination and grasping components, which are derived directly from the common 3D position data, after time normalisation. Excessive time normalisation is also prevented.
- 2) All selected landmarks are not mere convenient curve features such as zero crossing, extrema and inflexion point. Each selected landmark must be a relevant kinematic event (Helwig et al., 2011) that represents an underlying mechanism that affects the formation of the hand transport TV_{el} profile. This is achieved via wide literature review spanning neuroscience and rehabilitation science (Chapter 2) as well as detailed analyses of the effects of forearm supination and grasping on the hand transport TV_{el} (Chapter 3 and 5). This analysis is made possible because of the novel nonlinear time normalisation procedure proposed in Chapter 4. In the end, 4 landmarks are used to normalise the time of hand transport TV_{el} profiles. The procedure is denoted as NTN4 (Chapter 6).

- 3) A novel finding that the hand transport TVel profiles for the entire group of subjects can be divided into 3 and 7 groups for the CYL and CUBE tasks (Chapter 3) respectively is accomplished via the use of *k*-means unsupervised clustering algorithm (Chapter 6). This also reduces the temporal variance that resulted in erroneous inter-subject hand transport TVel amplitude variance.
- 4) A 95% prediction interval that is more accurate and sensitive in detecting deviation from normal hand transport TVel amplitude is constructed (Chapter 6 and 7). This is achieved by constructing normative hand transport EM_TV_{el} profiles, using the hand transport TVel profiles that are time normalised via the NTN4 procedure, for different groups of subjects for both CYL and CUBE tasks (Chapter 6).
- 5) Evaluation of patients' performance of 2 reach-to-grasp tasks is performed using the entire hand transport TVel profile instead of relying on specific kinematic parameters (Chapter 7). That is, a macroscopic evaluation is achieved instead of a microscopic one. In this way, movement quality of a reach-to-grasp task is assessed throughout the entire movement duration.
- 6) An objective measure of deviation from normal reach-to-grasp movement is proposed (Chapter 7). This is constructed based on normative data from healthy subjects as well as pathological data from patients.
- 7) The proposed UE assessment method is clinically relevant and can be easily implemented. This is achieved because of the following reasons:
 - i) The reach-to-grasp action is identified as one of the most performed activities of daily living and is also a common UE therapeutic and assessment task conducted clinically (Chapter 2). It is believed that a stroke patient's performance of a reach-to-grasp task gives a good indication to the recovery status of the affected UE.
 - ii) Based on evidences from neuroscience and motor control studies (Bueno et al., 2002; Flanagan & Rao, 1995; Schneiberg et al., 2002; Shadmehr & Wise, 2005; Winstein et al., 2003), hand transport TVel is believed to adequately (though not completely) characterise a reach-to-grasp task (Chapter 2).

Importantly, hand transport TVel is sensitive to pathological reach-to-grasp movements and can be easily obtained clinically.

- iii) The proposed objective assessment tool (Chapter 7) is intuitive as well as easy to construct and interpret. A therapist simply needs to determine the position of a patient's hand transport TVel profile on a *CORT-PIN* plot (Chapter 7). The distance between this position and a 'normal area' on the plot reflects the degree of deviation from normal reach-to-grasp movement.

8.2 Future work

Though much has been accomplished in this PhD study, it is acknowledged that more needs to be done before the proposed assessment tool can be implemented clinically. Hence, this section shall discuss some of these works.

8.2.1 *More detailed reach-to-grasp assessment*

As mentioned throughout this study, the hand transport TVel is just one of the many key kinematic parameters of a reach-to-grasp task that is regularly measured clinically and in research. Other parameters such as upper extremity ab-adduction angle, shoulder elevation, trunk movement in the sagittal plane etc. can also be monitored to give a more complete picture especially if detection of compensatory movements is one of the clinical assessment objectives. The procedures described in this study can be applied to obtain normative behaviour of these parameters. However, it should be cautioned that equipment requirement and patient preparation increase with an increase in the number of parameters monitored. Future research should thus be conducted to discover a critical set of parameters that provide an objective and clinically relevant assessment of a reach-to-grasp task. In other words, the assessment should lead to a meaningful design of appropriate interventions.

8.2.2 *Hand transport TVel profiles groupings*

In Chapter 6, 3 and 7 grouped normative hand transport EM_TVel profiles with NTN4 95% prediction intervals are constructed for the CYL and CUBE tasks respectively. These are based on only 16 subjects in this study. Due to the small subject sample size, 1 of the 3 CYL groups and 5 of the 7 CUBE groups have less than 3 subjects (Table 6.4 and 6.5). In terms of constructing normative hand transport EM_TVel profile, having too many small sized groups is not desirable as they tend not to be representative of the general population. Clearly, more

healthy subjects across all age groups should be added to the current group of subjects so that clustering can be performed based on a larger sample size. Theoretically, this should reduce the number of small sized groups thus increasing the accuracy of the 95% prediction interval. However, if these small sized groups persist, other options such as re-designing the feature space and/or implementing clustering techniques other than k -means algorithm may need to be considered.

8.2.3 Accuracy of *CORT-PIN* plot

The accuracy of *CORT-PIN* plot proposed in Section 7.3.1 is entirely dependent on the accuracy of the normative profiles that are used to define the *CORT* and *PIN* thresholds that in turn define the ‘normal area’. Once again, higher accuracy and representativeness of the normative profiles can be achieved with a larger sample size of healthy subjects. The minimum *CORT* threshold is defined by patient’s hand transport TVel profile’s position on the *CORT-PIN* plot. This threshold is supposed to identify patients with low level of UE recovery. Clearly, more data from patient with low level of UE recovery is required to verify and fine-tune the minimum *CORT* threshold.

8.2.4 Identifying expected groupings of patients

The biggest challenge in having different hand transport EM_TV_{el} curves for different groups of subjects is in deciding which group a stroke patient belongs to. This is a practical concern as it is unlikely that any stroke patient would have had his/her normal movement data collected prior to suffering from stroke. Fortunately, there are two possible solutions.

The first solution is to determine a set of physical and/or biomechanical parameters that may be common among healthy subjects within the same group. Statistical methods such as categorical dependent variable regression with nominal response can then be applied to express the grouping as a function of these parameters. In this way, a new stroke patient’s grouping can then be determined by these parameters. Obviously, for this method to work, the set of selected parameters must remain measurable or obtainable post stroke.

In the second solution, for each subject, hand transport EM_TV_{el} curves will be constructed for both dominant and non-dominant UEs using the NTN4 method. In this case, both the dominant and non-dominant hand transport EM_TV_{el} curves are to be used in the clustering process simultaneously. As a result, a functional relation between dominant and non-

dominant hand transport EM_TVels can be established. Consequently, the grouping of a stroke patient can be completely determined by his/her unaffected side's hand transport EM_TVel curve. This method conforms well to current clinical practise which therapist frequently relies on the performance of the unaffected UE as a gauge to monitor the recovery of the affected UE. This method improves current clinical practice by allowing therapist to monitor recovery of the affected UE directly with the expected movement quality of that UE once a patient's grouping has been determined.

8.2.5 *Making sense of CORT-PIN plot*

Knowledge of a patient's actual grouping is also useful in the context of the *CORT-PIN* plot. Obviously, with this knowledge, therapist is able to compare the patient's recovery against his/her expected normal movement and gain important information on how much more recovery can be expected. Besides, such knowledge will enable the detection of a possible change in control strategy as a patient recovers. For example, if it is known that a patient is supposed to belong to Grp A, but as the patient recovers, his/her hand transport TVel profile is observed to be more similar to the EM_TVel profile of Grp B. More research is needed to determine if this indicates a change in control strategy during the recovery process. This information has far fetching implications. It is conceivable that a change in movement control strategy in one arm will affect bilateral movements which require coordination of both arms. In such a case, the therapist may need to consider focusing more on bilateral training so that the less affected side can adapt to the affected side better.

Besides, future research can be directed towards understanding the underlying medical condition associated with specific (*CORT*, *PIN*) position and/or *DisNor* score to improve clinical interpretability. In this way, different intervention methods may be designed for patients belonging to different regions on the *CORT-PIN* plot.

8.2.6 *Temporal variance and its structure*

The focus of this study has been on developing an objective assessment of reach-to-grasp movement quality based on the amplitude behavior of hand transport TVel. In doing so, much of the temporal information is not being considered. As noted in Section 2.2, the temporal variance and its structure of the hand transport TVel curves may contain important information which should be considered in order to provide a more comprehensive and complete assessment of the reach-to-grasp movement (Stergiou & Decker, 2011). Stergiou et

al., (2004) provide a good coverage of nonlinear tools such as correlation dimension (CoD), Lyapunov exponent (LyE) and approximate entropy (ApEn) that have been used successfully in human movement studies to provide additional insights over those provided by traditional linear measures. In particular, ApEn which gives a measure of regularity of time series has been shown to be suitable even for small data sets with 50 to 5000 data points. This property will be particularly useful for clinical evaluation of patients who are most unlikely to tolerate lengthy assessment and thus only be able to provide short time series. Hence, future effort will be directed towards including nonlinear dynamic measures of the hand transport TVel curve to complement the proposed assessment procedure in this study.

8.2.7 Measurement instrument

Last but not least, any technological advancement needs to be mindful of the practical implementation issues, such as ease of use, so as to improve clinical viability. Hand transport TVel can be easily obtained via an inertial measurement unit (IMU) attached to the back of the hand. Measurement of angles on the other hand is more cumbersome. However, angular parameters may contain useful information to provide a more comprehensive movement assessment. Therefore, in conclusion, development of low cost, minimally intrusive and yet reliable measurement instrument for obtaining the required parameters remains a pertinent challenge.

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Appendix A

Results of nonlinear time normalisation on tangential velocity profiles

This appendix contains results of applying the nonlinear time normalisation procedure, proposed in Chapter 4, to normalise the time of hand transport tangential velocity (TVel) profiles for 1 typical subject performing TOU, SUP, CYL and CUBE tasks (refer to Section 3.2 for descriptions of these tasks). The results are organised according to task. That is, results for TOU are presented first, followed by SUP, then CYL and lastly CUBE. Please note that there are a total of 16 such sets of graphs (1 set per subject with each set containing graphs of 4 tasks), but due to space consideration, only 1 is presented here as illustration.

In the series of graphs, the left column contains hand transport TVel profiles for all iterations. There are a maximum of 10 profiles per iteration. In the right column, warping functions (one for each hand transport TVel profile) are shown for all iterations. Black arrow indicates the process of constructing the warping function using the corresponding set of hand transport TVel profiles (Step 2 and 3 in Section 4.1). White arrow indicates time normalisation in position domain that produces the new set of hand transport TVel profiles for the next iteration (Step 4 in Section 4.1). The process termination criterion is based on changes in amplitude variance between consecutive iterations (Step 5 and 6 in Section 4.1). This is shown in the tables at the end of each of these series of graphs.

Tables at the end of each series of graphs are results of comparing amplitude variance between 2 sets of hand transport TVel profiles for consecutive iterations (Step 5 and 6 in Section 4.1). 2-sample *t*-test is used to test the difference between the means of standard deviation (SD) between consecutive iterations. 2-sample Wilcoxon rank sum test is used to test the difference between the medians of SD between consecutive iterations. Negative values in columns 2 and 4 indicate a decrease in SD as compared to the previous iteration. Iteration is terminated when further iteration no longer makes any significant difference to the hand transport TVel amplitude variance. That is, for iteration > 1 , *p*-values in both 2-sample *t*-test and Wilcoxon rank sum test are > 0.05 (columns 3 and 5).

TOU task; Subject 10

Continue next page...

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Iteration	Difference in mean SD	<i>p</i> -value	Difference in median SD	<i>p</i> -value
1	0.001798	0.607909	0.007792	0.243257
2	-0.013453	0.000000	-0.014645	0.000000
3	0.003930	0.010854	0.003048	0.001749
4	-0.003122	0.037305	-0.000693	0.016131
5	0.000738	0.622130	-0.001363	0.976220

SUP task; Subject 10

Iteration	Difference in mean SD	<i>p</i> -value	Difference in median SD	<i>p</i> -value
1	-0.004940	0.035618	-0.004816	0.008912
2	0.000166	0.936173	0.000010	1.000000

CYL task; Subject 10

Iteration	Difference in mean SD	<i>p</i> -value	Difference in median SD	<i>p</i> -value
1	-0.052213	0.000000	-0.049033	0.000115
2	-0.007294	0.005686	-0.015212	0.010154
3	0.000000	1.000000	0.000000	1.000000

CUBE task; Subject 10

Iteration	Difference in mean SD	<i>p</i> -value	Difference in median SD	<i>p</i> -value
1	-0.016504	0.000036	-0.011765	0.000041
2	-0.000042	0.985983	0.000113	0.991351

Appendix B

Hand transport EM_TVel curves comparison across tasks

This appendix consists of plots of hand transport EM_TVel curves for all 4 task for each subject. Note that the EM_TVel curves for all 4 tasks are time normalised to 100% movement duration so as to facilitate comparison. Blue: TOU; Red: SUP; Magenta: CYL; Black: CUBE.

Appendix C

Supplementary material for adaptive Neyman test

C-1 Fourier coefficients of hand transport TVel profiles

The hand transport TVel profiles for each task (TOU, SUP, CYL and CUBE defined in Chapter 3) are subjected to discrete Fourier transformation. For each subject, the absolute values of the Fourier coefficients (vertical axis) are plotted against the coefficient position (horizontal axis) shown in the following graphs. Blue: TOU; Red: SUP; Magenta: CYL; Black: CUBE. For subjects 9, 12 and 14, the absolute Fourier coefficients seem to approach zero beyond the 19th coefficient. Therefore the maximum number of Fourier coefficients to be used in the adaptive Neyman test (Section 5.2.1.1) is set at 19.

C-2

Calculation of p -values for adaptive Neyman test

In this section of this appendix, the p -values for the adaptive Neyman (ANey) test described in Section 5.2.1.1 will be estimated based on the finite sample distribution of the distribution of T_{AN} under the null hypothesis based on 1 million simulations (Table C-2.1). A plot of T_{AN} against α for each sample size (n) is shown in Figure C-2.1. It is observed that each of these plots can be modelled as

$$\alpha = 1 - e^{-e^{a(T_{AN})+b}} \quad (C.1)$$

where a and b are parameters to be determined. Nonlinear regression modelling with the model in Eq C.1 is performed in MATLAB. The resulting values of a and b for each sample size (n) are shown in Table C-2.2. Based on these, values of a and b for sample size (n) not found in Table C-2.2 are interpolated using piecewise cubic Hermite interpolating polynomial via the MATLAB function ‘pchip’. With these, the p -value (α) for any given pair of n and T_{AN} values can be estimated using Eq C.1.

Table C-2.1: α upper quantile of the distribution of T_{AN} under the null hypothesis (Section 5.2.1.1) based on 1 million simulations. (Source: Fan & Lin, 1998)

n/α	0.00001	0.00005	0.0001	0.00025	0.0005	0.001	0.0025	0.005	0.01	0.025	0.05	0.1	0.25	0.5
5	12.45	11.39	10.55	9.42	8.65	7.8	6.74	5.97	5.21	4.23	3.5	2.77	1.77	0.96
10	16.53	13.91	12.79	11.53	10.47	9.13	7.73	6.77	5.78	4.57	3.67	2.74	1.49	0.4
20	16.82	14.88	13.95	12.49	11.27	9.83	8.26	7.16	6.07	4.75	3.77	2.78	1.41	0.18
30	17.58	15.47	14.62	12.9	11.65	10.11	8.47	7.29	6.18	4.82	3.83	2.81	1.39	0.11
40	18.71	16.11	15.14	13.34	11.92	10.34	8.65	7.41	6.22	4.87	3.85	2.82	1.39	0.08
50	19.85	16.08	15.15	13.35	11.89	10.32	8.67	7.43	6.28	4.89	3.86	2.84	1.39	0.07
60	18.45	16.25	15.26	13.53	12.16	10.56	8.8	7.51	6.32	4.91	3.88	2.85	1.39	0.07
70	20.37	17.04	15.4	13.65	12.27	10.59	8.81	7.55	6.34	4.92	3.88	2.85	1.4	0.06
80	20.46	16.24	15.17	13.68	12.24	10.54	8.81	7.57	6.37	4.93	3.89	2.85	1.4	0.06
90	21.84	17.67	15.78	14.06	12.62	10.79	8.95	7.65	6.4	4.94	3.9	2.86	1.4	0.06
100	20.73	17.37	15.87	14.12	12.59	10.8	8.95	7.65	6.41	4.95	3.9	2.86	1.41	0.06
120	20.02	16.99	15.87	14.19	12.77	10.87	8.96	7.65	6.41	4.95	3.9	2.87	1.41	0.05
140	21.08	17.14	15.98	14.08	12.43	10.8	9	7.66	6.42	4.95	3.9	2.86	1.41	0.05
160	19.42	17.07	16.19	14.4	12.97	10.88	8.95	7.69	6.42	4.95	3.91	2.87	1.41	0.06
180	21.33	17.71	16.14	14.5	12.97	11.02	9.1	7.77	6.47	4.95	3.9	2.87	1.41	0.06
200	20.5	17.51	16.34	14.31	12.78	11.1	9.08	7.72	6.43	4.95	3.89	2.86	1.42	0.06

Figure C-2.1: Graphs of T_{AN} against α for each sample size based on values in Table B-2.1. The legend denotes the sample sizes of the graphs.

Table C-2.2: Values of a and b for each sample size (n) based on nonlinear regression with Eq C.1.

n	a	b
5	1.047	0.6324
10	0.8021	-0.04691
20	0.7214	-0.2352
30	0.6952	-0.2881
40	0.6833	-0.3089
50	0.6777	-0.3161
60	0.6757	-0.3168
70	0.671	-0.3226
80	0.6704	-0.3228
90	0.6689	-0.3232
100	0.6643	-0.3289
120	0.6635	-0.329
140	0.6643	-0.3289
160	0.666	-0.3229
180	0.6662	-0.3228
200	0.666	-0.3217

Appendix D

Plots of occurrences of SupE and AperE

This appendix presents the occurrences of SupE (Eq 6.1a) and AperE (Eq 6.1b) as indicated by the triangle and circle markers, respectively, on the hand transport TVel plot for each subject. The plots for the CYL task are presented for each subject followed by that of the CUBE task.

D-1

CYL task plots

D-2

CUBE task plots

SupE & AperE on Hand Transport TVel(NTN)
Subject 15 Condition CUBE

SupE & AperE on Hand Transport TVel(NTN)
Subject 16 Condition CUBE

Appendix E

Hand transport EM_TVel profiles and 95% prediction intervals for CYL and CUBE tasks

This appendix contains Table E.1 and E.2 that consist of hand transport EM_TVel plots for the CYL and CUBE tasks respectively. Each table contains 2 columns. Plots in the first column consist of hand transport EM_TVel plots subjected to NTN (cyan), LTN (black) and NTN4 (red). Plots in the second column consist of hand transport EM_TVel plots subjected to NTN (cyan), LTN (black) and NTN5 (red). Each row consists of plots for each subject. On each plot, the solid curves denote the EM_TVel curves and the dotted curves denote the resulting 95% prediction intervals.

Table E.1: Hand transport EM_TVel profiles and 95% prediction intervals for CYL task.

Table E.2: Hand transport EM_T Tvel profiles and 95% prediction intervals for CUBE task.

Appendix F

Silhouette value plots of *k*-means clustering for CYL and CUBE tasks

This appendix contains the silhouette value plots of the *k*-means clustering for the CYL and CUBE tasks. For the CYL task, the number of clusters range from 2 to 7. For the CUBE task, the number of clusters range from 2 to 9. These results are collected in Table F.1. Note that these silhouette value plots are meant to supplement the silhouette statistics and gap statistics in determining the optimal number of clusters via the *k*-means algorithm (Section 6.2.2.1 and 6.2.2.2). Clustering with negative value on silhouette plot is not selected as negative value on silhouette plot implies possibility of wrong clustering.

Table F.1: Silhouette value plots of *k*-means clustering for CYL and CUBE tasks.