Decoding human motion intention using myoelectric signals for assistive technologies

Antuvan, Chris Wilson

2019

Antuvan, C. W. (2019). Decoding human motion intention using myoelectric signals for assistive technologies. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/88684>

<https://doi.org/10.32657/10220/48046>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**Decoding Human Motion Intention using Myoelectric Signals for
Assistive Technologies**

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A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

Statement of originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

Date : 16-April-2019

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Author attribution statement

This thesis contains material from four papers published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as Chris Wilson Antuvan, Federica Bisio, Francesca Marini, Shih-Cheng Yen, Erik Cambria, and Lorenzo Masia. "Role of muscle synergies in real-time classification of upper limb motions using extreme learning machines." *Journal of neuroengineering and rehabilitation* 13, no. 1 (2016): 76. doi.org/10.1186/s12984-016-0183-0

The contributions of the co-authors are as follows:

- Assoc/Prof Masia provided the project direction and edited the manuscript drafts.
- I prepared the manuscript drafts.
- I conceived the idea, designed the study and performed the experimentation. I also analyzed and interpreted the data.
- Federica Bisio assisted in implementing the experiment, and in revising the manuscript content.
- Francesca Marini FM helped in analyzing and interpreting the data, and in revising the manuscript content.
- Ass/Prof Erik Cambria assisted in conceiving the idea and in revising the manuscript content.
- Assoc/Prof Shih-Cheng Yen assisted in conceiving the idea and in revising the manuscript content.

Chapter 4 is published as Chris Wilson Antuvan, and Lorenzo Masia. "An LDA-based Approach for Real-Time Simultaneous Classification of Movements using Surface Electromyography." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* (2019). doi.org/10.1109/TNSRE.2018.2873839

The contributions of the co-authors are as follows:

- Assoc/Prof Masia provided the project direction and edited the manuscript drafts.

- I prepared the manuscript drafts.
- I conceived the idea, designed the study and performed the experimentation.
I also analyzed and interpreted the data.

Chapter 5 is published as Chris Wilson Antuvan, and Lorenzo Masia. "Position and stiffness modulation of a wrist haptic device using myoelectric interface." In 2017 International Conference on Rehabilitation Robotics (ICORR), pp. 734-739. IEEE, 2017. doi.org/10.1109/ICORR.2017.8009335

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Date : 16-April-2019

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[Chris Wilson Antuvan]

Acknowledgements

It has been an amazing four-year journey, roller-coasting through the ups and downs in my research work, but nevertheless has been an incredible experience in my life, filled with wonderful memories. I am immensely grateful to my supervisors Prof. Lorenzo Masia and Prof. Dino Accoto for giving me the opportunity to pursue my doctoral studies at the ARIES lab in NTU. Thanks for mentoring me with your valuable experience and giving me the freedom to pursue my research interests. I would also like to thank my co-supervisors who are part of my thesis advisory committee, for being there to review my progress and providing valuable feedback. Next, I would like to thank the Robotics Research Center staffs for always being there to assist in the admin related tasks and in the timely order of the instruments and parts for my experiments. Next, I would like to thank my colleagues from the lab, Leo, Sara, Khanh, Michele, Angelo, Yongtae, Carlo, Asif, Aamani, Paolo and Simone for their constant encouragement and support. I would also like to thank all the subjects who have helped me in performing the experiments and helping provide valuable data for my research. Lastly, I would like to thank my parents and siblings, for their love and affection. It wouldn't have been possible without your support.

Abstract

Diseases or trauma affecting either the sensory or motor functions in humans leads to movement impairment. They severely affect the independence of the user and the ability to perform activities of daily living. Assistive technologies aim to function in parallel to the affected human body and provide assistance. However, it is important for the robots to understand the user's motion intention so as to provide assistance in the desired movement; the intention detection is especially challenging in the case of upper-limb motions which are primarily involved in performing dexterous manipulation tasks. Myoelectric signals are capable of providing relevant information about the intent of motion and the extent of effort applied by a person. As such, it is a practically viable solution to utilize electromyographic (EMG) signals to build intuitive human-machine interfaces for applications in prosthetics, orthotics, tele-manipulation and functional electrical stimulation. However, there are quite a lot of challenges with regards to reliably translating the human intention for functional use and efficient control of a multifunctional device. The primary reason is that the EMG signals are time-varying and noisy. Moreover, there is a complex non-linear relationship between the numerous muscles and the corresponding output forces. The aim of this thesis is in providing improvements and solutions to some of the limitations in decoding myoelectric signals, and the work is centered around four themes with focus on the upper limb motions. The first goal is to identify strategies for improving the reliability of myoelectric-based motion decoding. We explored the use of extreme learning machines and quantified its performance for online decoding and evaluating the differences in accuracy while using both muscle synergy and time-domain based features. Secondly, our focus is on building efficient algorithms by using dimensionality reduction techniques to simplify the control com-

plexity; we explored the use of non-negative matrix factorization and linear discriminant analysis for improving and enhancing the decoding capability of EMG-based control interfaces. The third objective is to incorporate simultaneous decoding capability, thereby enable dexterous control of the device by the user. We developed and evaluated the decoding performance of an algorithm capable of classifying both simple and compound movements, by recording only the EMG activity associated to simple movements. The final goal is to implement a user-modulated position and stiffness control of an exoskeleton device, to transfer the impedance characteristics of the human to the device, thereby enabling better transparency and safety in applications involving human-machine interactions. We evaluated the efficacy of simple models to identify the stiffness characteristics from the user's EMG signals, in a trajectory tracking task.

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List of Publications

The various works presented in this thesis have been published, and the contents are taken from some of the following articles.

Journals

- **Antuvan, Chris Wilson**, and Lorenzo Masia. "An LDA-based Approach for Real-Time Simultaneous Classification of Movements using Surface Electromyography." IEEE Transactions on Neural Systems and Rehabilitation Engineering (2019)
- **Antuvan, Chris Wilson**, Federica Bisio, Francesca Marini, Shih-Cheng Yen, Erik Cambria, and Lorenzo Masia. "Role of muscle synergies in real-time classification of upper limb motions using extreme learning machines." Journal of neuroengineering and rehabilitation 13, no. 1 (2016): 76.
- Dinh, Binh Khanh, Michele Xiloyannis, **Chris Wilson Antuvan**, Leonardo Cappello, and Lorenzo Masia. "Hierarchical cascade controller for assistance modulation in a soft wearable arm exoskeleton." IEEE Robot. Autom. Lett. 2, no. 3 (2017): 1786-1793.
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2015 37th Annual International Conference of the IEEE, pp. 6732-6735. IEEE, 2015.

- D. Chiaradia, M. Xiloyannis, **C. W. Antuvan**, A. Frisoli and L. Masia, "Design and embedded control of a soft elbow exosuit," 2018 IEEE International Conference on Soft Robotics (RoboSoft), Livorno, 2018, pp. 565-571.

Book Chapters

- Xiloyannis, Michele, Leonardo Cappello, B. Khanh Dinh, **Chris Wilson Antuvan**, and Lorenzo Masia. "Design and Preliminary Testing of a Soft Exosuit for Assisting Elbow Movements and Hand Grasping." In *Converging Clinical and Engineering Research on Neurorehabilitation II*, pp. 557-561. Springer, Cham, 2017.
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- Masia, L., Hussain, I., Xiloyannis, M., Pacchierotti, C., Cappello, L., Malvezzi, M., Spagnoletti, G., **Antuvan, C.**, Khanh, D., Pozzi, M. and Prattichizzo, D., 2018. *Soft wearable assistive robotics: exosuits and supernumerary limbs*.

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Chapter 1

Introduction

The use of electromyography (EMG) for human motion intention decoding has found potential in a wide variety of applications, including prosthesis [7, 8, 9], orthotics (exoskeletons) [10, 11, 12], tele-manipulation [13, 14, 15, 16], and functional electrical stimulation [17, 18], mainly because of the intuitive nature and reduced cognitive burden offered by the control interface to the humans. EMG signals are considered as a useful proxy to the electrical activity originating from the brain, but unlike brain activations, muscle signals are only produced when there is actual muscle contraction; isotonic contractions result in movement of the limbs, whereas isometric contractions result in static posture holding. The advent of non-invasive techniques termed as surface electromyography (sEMG) to detect and measure the electrical activity of the muscles from the surface of the skin, have led to an increased utilization of myoelectric-based interfaces in a wider variety of population and applications. Nevertheless, the ultimate goal in robotics applications using myoelectric-based interfaces for decoding the movement intention, is to help restore lost functionality in the case of amputees, assist/augment the motion in the case of impaired/healthy people, or remotely control the motion of a device.

Recent advances in actuator technology have enabled prosthetic and exoskeleton devices to include multiple degrees-of-freedom (DOFs) with capability to perform sophisticated movements [19, 20, 21, 22, 23]. Moreover, robotic devices have also evolved from being stiff and rigid in nature to be more compliant in order to ensure

a safer interaction with the humans and enhance the capability to perform collaborative tasks [24, 25, 26, 27]. The challenge however, is to build intuitive control algorithms to enable independent and reliable real-time control of the numerous DOFs, as well as adapt the level of compliance depending on the nature of the task, using the myoelectric signals produced by the user.

1.1 Motivation and Objective

1.1.1 Improve reliability and robustness of motion decoding

Decoding human motion intention using myoelectric signals have been in development since the early 1960s [28, 29]. Yet, after so many decades, research on myoelectric-based interfaces meant to help people with disabilities, hasn't gone past clinical testing, and found proper functional use by the affected patients [30]. As much as the muscle activation signals are capable of providing useful information about the user's movement characteristics, the more difficult it is to extract them reliably and robustly.

The primary reason is that sEMG signals are noisy and time-varying, and are subject to variations with sweat, muscle fatigue and slight shift in electrode positions [31]. Using surface electromyography also poses issues related to cross-talk in the signals (EMG activity from nearby muscles) and difficulty in accessing deeper muscles, hence making it challenging to place an electrode and record the activity of only a specific muscle [32]. Certain feature extraction procedures are capable of identifying synergistic trends in the muscle activity patterns of a group of muscles that are collectively responsible for a compound movement; these features have shown to produce robust signals to slight shifts in electrode position, and are capable of capturing the coordinated patterns of the various muscles while performing smooth and fluidic movements involving multiple DOFs [33]. Therefore, one of the primary objectives of this work is to identify techniques that can extract reliable information and mitigate the limitations of surface electromyography.

Machine learning techniques are generally employed to build a model relating the in-

put muscle activity with the output motions; they play a significant role in determining the robustness of decoding, and influences the prediction accuracy, the learning rate, and real-time operating speeds [34]. Any learning algorithm is only as good as the quality of the data (choice of the feature extraction process) used, and can directly influence on the performance of the decoder [35]. However, it is also important to use a learning scheme which has better capability of generalizing to unseen data, for ensuring robustness in decoding. Calibration periods for training a decoder depends mainly on the quantity of data as well as the learning speed of the algorithm. Therefore, to minimize the time for calibration of the decoder, it is important to use algorithms which have faster learning rates. The speed of classification is also important to ensure better performance for real-time decoding of motions [36]. Hence, another goal is to test the performance of a learning algorithm which can cater to the needs of real-time decoding of motion intention.

1.1.2 Embedded control architecture

An important aspect that can motivate the clinical patients in using assistive and prosthetic devices for daily life activities, is the form factor and cosmetic appearance of the mechatronic components [30]. Recent trends in assistive technologies have indicated a paradigm shift from bulky and rigid exoskeletons to soft, fabric-based wearable exosuits; these exosuits aids in creating a low-profile outlook to the user and prevents hindrance of the natural movement of the limbs, that are prone to occur due to the rigid constraints in the case of rigid exoskeletons [24, 25, 26, 27]. However, a great deal of advancements is necessary to match the control capabilities of rigid exoskeletons, due to the compliant nature and inherent non-linearities in the dynamical model.

Advances in semiconductor technologies have facilitated in diminishing the size of the processing units, thereby reducing the form factor and enabling portability of the processing units of these devices, but they are still limited in terms of computational power compared to the traditional processors [37, 38]. Therefore, it is critical in developing computationally efficient algorithms for effective real-time control of these devices. Reducing the dimensionality of the input commands helps in simplifying

the control complexity and lowering the computational cost; more specifically it is essential to identify synergistic patterns in the input command space (either muscle activity or kinematics), which can aid in the development of efficient control algorithms [39]. This strategy is mainly inspired by the way the brain is hypothesized to coordinate and control the activations of the numerous muscles and produce a synchronized motion of the multiple DOFs [40]. In this context, our objective is in exploring the use of dimensionality reduction techniques in efficiently decoding myoelectric signals.

1.1.3 Simultaneous classification of movements

Tasks demanding dexterous manipulation involves concurrent actuation of more than one DOF; when we reach for an object, we simultaneously adjust the wrist orientation and the hand posture rather than doing it in sequence. The capability to simultaneously decode multiple motions is considered to be an intuitive and natural strategy, compared to sequential prediction of movements [41, 42]. The decoding becomes particularly demanding in the case of joints with multiple DOFs, especially distal joints such as the wrist and hand where the relationship between the various muscles and the movements are complex and non-linear [43]. This further makes the simultaneous decoding of movements challenging, demanding longer calibration phases and requiring enhanced machine learning techniques. Moreover, muscle activity features of the combined movements are hypothesized to be linear mixture of the feature vectors of the respective individual motions [44], which could aid in simplifying the calibration process for the user. Our aim is to develop an algorithm which has the capability to simultaneously decode more than one motion at the same instant, by developing an algorithm which can discriminate both simple and compound movements, but by recording the EMG signals of only the simple motions.

1.1.4 Safer human-robot interaction

Humans have the inherent capability to modulate the impedance characteristics in the joints depending on the nature of the task [45, 46, 47, 48, 49, 50]. This allows for safer interaction with the external environment and efficient task performance [47]. Exoskeleton devices generally use joint position [51] or force measurements [52] to identify the intent of the user, but these control architectures are not capable of adapting to unknown and changing external environment, thereby affecting the efficacy of task performance. This has led to the need for integrating myoelectric signals which can aid in identifying and transferring the impedance characteristics of humans to the robotic device, thereby enabling a more transparent and safer interaction, especially in the case of exoskeletons [53]. Modulation of impedance characteristics using the EMG signals have generally been implemented in the case of a prosthetic device or for tele-operation in a robotic arm [54, 55, 56]. However, the concept of an user-modulated impedance control has not been explored much in case of an exoskeleton, especially for the upper-limb. Therefore, our objective is to implement an impedance control architecture to enable the modulation of the dynamical parameters of an orthotic device in real-time using a myoelectric interface.

1.2 Thesis Outline and Contribution

Chapter 2 includes the background literature regarding electromyography and the pre-processing techniques. The various motion intention detection techniques including the various feature extraction methods and the learning algorithms in building a decoding model is presented. This is followed by the various strategies that were developed in the past, to perform simultaneous decoding of movements. The concept of muscle synergies and its use in the context of myoelectric control is also presented.

Chapter 3 focuses on the role of muscle synergy based features in the real-time decoding of upper-limb motions, by evaluating and comparing the key performance differences while using time-domain based features. The potential for using extreme learning machines (ELM) in myoelectric control is explored by evaluating the decod-

ing performance in both offline and online scenario.

Chapter 4 introduces a novel decoding strategy for incorporating simultaneous decoding using linear discriminant analysis technique. The algorithm is capable of discriminating both individual and combined movements, by recording the EMG data from only the individual motions. The performance of this model is evaluated for online decoding for a simple two-DOF motion involving the wrist and hand movements.

Chapter 5 presents a preliminary study to implement a simplified linear control architecture for real-time modulation of position and stiffness characteristics in an orthotic device controlled via the user's myoelectric signals. User-performance is evaluated in a trajectory-tracking task in a varying force field for a one-dimensional wrist flexion/extension motion. Assessment of the performance with regards to similarity with previous studies involving tele-manipulation in a prosthetic device is confirmed in this study.

Chapter 6 summarizes the important contributions of this thesis, and presents an overlook on future directions of research.

Chapter 2

Background Literature

2.1 Electromyography

Electromyography (EMG) is a technique concerned with the recording and analysis of myoelectric signals. Myoelectric signals are formed by physiological variations in the state of muscle fiber membranes [1]. Besides physiological and biomechanical studies, electromyography has found applications in various fields of research like rehabilitation, sports science and ergonomics as shown in Fig.2.1. The amplitude of the EMG signal after rectification and smoothening is related to the force or torque exerted by the subject. However, there are a lot of factors which influence the EMG signal like physiological, anatomical, as well as technical aspects that have to do with its recording. It is not possible to regulate all these factors with the current technology[2]. The factors that influence the EMG signal can be broadly classified into three categories, as indicated in Fig. 2.2:

1. **Causative:** Causative factors are those which have the elemental effect on the signal. This is further divided into *Extrinsic* and *Intrinsic*. Extrinsic factors include 1) The electrode configuration 2) location of the electrode with respect to the motor points on the muscle 3) location of the electrode on the surface of the muscle and 4) orientation of the detection surfaces with respect to the muscle fibers. The Intrinsic factors include 1) number of active motor units at any particular time of the contraction 2) fiber type composition of the muscle

Figure 2.1: Applications of electromyography [1].

3) blood flow in the muscle 4) fiber diameter 5) depth and location of the active fibers within the muscle with respect to the electrode detection surfaces 6) the amount of tissue between the surface of the muscle and the electrode and 7) other factors that are yet to be identified, such as the length of the depolarization zone and ionic fluxes across the membrane, etc.

2. **Intermediate:** Intermediate factors are those physical and physiological phenomena which are influenced by one or more of the *Causative* factors, and also influence the *Deterministic* factors. They include 1) the band-pass filtering aspects of the electrode 2) the detection volume of the electrode 3) superposition of action potentials in the detected EMG signal 4) crosstalk from nearby muscles 5) the conduction velocity of the action potentials that propagate along the muscle fiber membrane and 6) the spatial filtering effect due to the relative position of the electrode and the active muscle fibers.
3. **Deterministic:** Deterministic factors are those which have a direct relationship with the EMG signal and the recorded force. They include 1) the number of active motor units 2) the motor unit force-twitch 3) the mechanical interaction between muscle fibers 4) the motor unit firing rate 5) the number of detected

motor units 6) the amplitude, duration and shape of the motor unit action potentials and 7) the recruitment stability of motor units.

Figure 2.2: A schematic diagram of the factors which affect the EMG signal [2].

2.2 EMG Pre-processing Techniques

Raw EMG signals provide good qualitative indications of the muscle activity, but for a more quantitative analysis, a series of signal processing procedures have to be performed to have a more reliable measure for utilization in subsequent steps. EMG signals in general contain a lot of high frequency sensor noise and should be removed. The main steps involved in the processing of raw EMG signals are outlined below.

2.2.1 Full wave rectification

The first step involves rectification of the signal amplitude to obtain only positive values. It is represented by

$$|x| = \begin{cases} x, & x \geq 0 \\ -x, & x < 0 \end{cases} \quad (2.1)$$

Figure 2.3: EMG rectification[1]

2.2.2 Linear enveloping

The second step is to obtain a linear envelope of the rectified EMG signal, which provides information about the amplitude of the waveform and gives an estimate of the contraction levels of the subject. There are three methods to obtain the linear envelope of the signal:

1. **Moving Average:** A sliding time window consisting of a specific number of samples is defined, and the average of the rectified EMG values in used to determine the amplitude of the signal at each instant in the moving frame. The greater the size of the window, the higher the risk of a phase shift in the EMG activity.
2. **Root mean square:** The root mean square value of the EMG signal in a sliding window frame is used to determine the amplitude of the signal in the moving frame. It generally reflects the mean power of the signal.

3. **Low-pass filter:** The EMG signal is passed through a low-pass filter such as a Butterworth filter to remove the high frequency noise and obtain the envelope of the signal. The advantage of using higher order filters is that it can be applied recursively to minimize the phase shift phenomenon.

Figure 2.4 shows the three types of linear enveloping methods applied to the rectified EMG signal.

Figure 2.4: The application of the three linear enveloping methods on the rectified EMG signal obtained from the biceps brachii muscle is shown in the plot [3].

2.3 Motion Intention Detection Techniques

The simplest and straight forward way to decode motion intention using sEMG signals is by placing the electrode directly on the belly of the muscle and map the amplitude of the signal produced to trigger a particular motion [57]. The movement could be either discrete (on/off) by setting a threshold for muscle activity, or analogous by scaling the amplitude of the signal to vary proportionally with either the kinematics or force outputs. An extension of this method termed parallel dual-site control was introduced to use an agonist/antagonist muscle pair to control the motion of a physiologically appropriate DOF or a one-dimensional motion of a virtual

Figure 2.5: Pattern recognition schematics for training and testing phase.

object [58, 59]. But it becomes quite challenging when it comes to decoding multiple DOFs in a single joint due to the complicated relationship between muscle activity and the corresponding motion [60]. There doesn't exist a one-to-one relationship between muscle activity and output motions, and thereby the above mentioned schemes cannot be applied for controlling multiple DOFs. Moreover, the use of surface electromyographic techniques require accurate electrode positioning, to minimize the cross-talk in the muscle activity, and has limitations in accessing deeper muscles [61, 31]. This led to the introduction of pattern recognition based techniques which use machine learning algorithms to build a non-linear relationship between the input muscle activity and the output motions [62, 63, 64, 65, 66]. It generally consists of a training phase where the EMG activity and the corresponding output parameters are recorded, to calibrate the decoder. The performance of the decoder is then evaluated during the testing phase either for offline or online testing using a new set of data. A general schematic of the pattern recognition method is shown in figure 2.5. Another drawback with using surface electromyography is that the signals are highly non-stationary, and are prone to degradation with slight shift in electrode positions, sweat, and muscle fatigue [30]. Therefore it becomes necessary to re-calibrate the decoder, each time a new user or even the same user needs to use the device, owing to inter and intra-subject variability in the EMG signals.

2.3.1 Feature extraction techniques

There are a wide variety of feature extraction techniques that are applied in order to obtain useful information from the EMG signals. It is important to identify features which are robust and reliable, and can provide information pertinent to the corresponding task/motion performed by the user. These techniques can be broadly classified into two types as reported by Ison et al. [35]:

1. **EMG features:** These extract information from each EMG channels separately. They can be further classified into time domain, frequency domain and time-frequency domain features [67, 68, 69].

Time domain features are based on signal amplitude, proportional to the number and rate of activation of motor units [67]. Some features such as zero crossings and slope sign changes, give some frequency related features, but without performing any frequency domain transforms. But otherwise, these features indicate signal energy, activation level, duration of contraction and a relationship to force output [70]. The time-domain features generally used in pattern recognition algorithms employ variations of Hudgin's original set [71, 72, 73].

Frequency domain features look into information regarding the rate and shape of the motor unit action potentials [74, 75, 76]. Though, these features require higher computational costs compared to the time domain features, study has also shown that former feature sets do not significantly improve the performance over the latter ones [75].

Time-frequency features identify transient as well as steady state patterns of the muscle contractions [77, 63]. These features generally transform the signals to a higher dimensional space such as the multiresolution analysis with wavelets and can provide lot more information compared to above mentioned features [67]. However, the extraction of these features are computationally very high and generally not suitable for real-time applications [35].

2. **Synergy features:** These features are evaluated by processing the EMG channels collectively, and provide information regarding the underlying principles

of muscle coordination patterns while performing compound movements [78, 79]. Though the synergy features help in reducing the dimensionality of control, the extent to which the entire EMG activity patterns are described, depends on the number of and composition of the synergies [80, 81]. Synergy features are inherently robust to amplitude cancellation, and help in simplifying the control complexity [39]. They are further classified into feature projection and spatial filtering based features.

Feature projection techniques transform the EMG signals to a low-dimensional subspace, providing coordination patterns of the muscle activation for a specific compound movement. A wide variety of techniques namely non-negative matrix factorization (NMF), principal component analysis (PCA), independent component analysis (ICA), linear discriminant analysis (LDA), clustering and non-linear projections are used to extract these features.

2.3.2 Learning algorithms

The learning algorithm plays a crucial role in determining the prediction accuracy of the output. However, the robustness and reliability of the decoding depends also on the quality and quantity of the data-set obtained during calibration, and on the ability of the learning algorithm to generalize to unseen data [30]. The quantity of the data obtained to train the decoder has a direct influence on the calibration time-period, whereas the quality of the data is related to the type of feature extraction procedures used, and influences the speed of operation in real-time control. Therefore, it is essential to employ an algorithm which has a faster rate of learning to minimize calibration time-periods, and has the computational capability to perform faster real-time operations, thereby ensuring a seamless closed-loop control of any mechatronic device using myoelectric interfaces.

Decoding schemes can be either classification or regression based depending on the control requirement. Classification schemes involves providing discrete output (on/off), whereas regression schemes generate continuous and proportional outputs; the latter strategy is generally more challenging and complicated compared to

the former one. However, there are pros and cons in using both these strategies. Classification schemes are capable of decoding multiple gestures/ movements without compromising much on the prediction accuracy [67, 82]. However, they are mostly limited to performing only sequential decoding, unless otherwise recording the EMG data of the simultaneous motion (combination of more than one motion) as a separate class, in which case the total number of classes (both individual and simultaneous) increases exponentially with the number of individual classes, leading to an increased calibration time. Regression schemes are mostly preferred in exoskeleton applications where the robotic device is required to follow the human movements accurately enough and provide assistance [83]. They are capable of simultaneous and proportional control of multiple DOFs, but due to the complex relationship between muscle activity and output forces, and owing to the drawbacks of using surface electromyography, usage is generally limited to two or three DOFs for better reliability of decoding [31, 84].

2.4 Simultaneous Decoding

Extending the myoelectric control to include simultaneous control of multiple DOFs, can be broadly grouped depending on using either linear or non-linear controllers, and some of them can be used to perform both classification and regression schemes:

2.4.1 Linear controllers:

These include algorithms which are computationally efficient and mostly involves using synergistic approaches to simplify the dimensionality of control [85, 86].

1. **Linear regression (LR):** It is the most simplified version, and involves training a linear regression model to map EMG feature vectors to the corresponding output position/force [87]. However, this strategy requires the data from both individual and simultaneous motions, and cannot accurately model the relationship between the muscle activity and the output motion since it is complex and non-linear.

2. **Linear discriminant analysis (LDA):** It is a supervised algorithm and extracts task-specific synergies, which can be directly used to discriminate between various motions [88]. This strategy can be used to build a single classifier using LDA to decode simultaneous movements, provided data from both individual and combined movements are recorded during the calibration phase [89, 90]. Moreover, modified versions of this model were introduced; 'parallel scheme' by Baker et al. [91], and 'conditional parallel' by Young et al. [92], to improve the decoding accuracy.
3. **Linear time invariant (LTI) models:** It involves performing a feature projection which could potentially provide better linear relationship between the input and the output in the transformed space. Artemiadis et al used principal component analysis (PCA) to project both the input EMG signals and the output joint positions, to a lower dimensional space, followed by using a maximum likelihood algorithm to build the linear decoding model [93, 94].
4. **Non-negative matrix factorization (NMF):** This algorithm is used to perform a feature transformation of the EMG signals, and can be directly employed to perform simultaneous and proportional control of two or three DOFs, without the need for any regression algorithms [95, 96]. The strategy proposed by Jiang et al., involves performing NMF decomposition algorithm on each DOF separately, to obtain a pair of synergy vectors for each direction of the concerned DOF. The synergy vectors corresponding to each DOF are linearly mixed to perform simultaneous and proportional decoding of multiple DOFs [41].

2.4.2 Non-linear controllers

They have the ability to build complex relationship between input EMG signals and the output motions. But there are high chances of overfitting the model to the training data, and lack generalization to unseen data [97].

1. **Support vector machines (SVM):** They identify a hyperplane to separate data from one class with another; kernel functions can be used to obtain a non-linear transformation of the input space, and also in a higher dimensional space

to allow for better separation of the data between various classes [98]. However, SVM algorithm does not support dual association, i.e. wrist flexion & hand close is a separate class from wrist flexion. Therefore a one-versus-one [99] or one-versus-all [100] strategy is used to identify an hyperplane separating both the classes belonging to both individual and combined movements; the class having the most number of predictions is the final output. Regression models based on SVM have also been introduced which supports dual association by building one model per DOF [101].

2. **Artificial neural networks (ANN):** It consists of a multi-layer perceptron (MLP) with weights relating each of the nodes from one layer to another, and uses non-linear transformations at each node [102, 103, 104, 105, 106]. A learning algorithm based on backpropagation technique is generally used to train the model and assign the weights [97, 107]. Unlike SVM, ANN supports dual association, where an MLP model can be trained for each DOF to perform simultaneous classification, and can also be extended to incorporate proportional control [108, 109, 110].
3. **Other non-linear controllers:** These include Gaussian mixture models [111], random forests [112], K-nearest neighbours [113], Hill-based muscle models [114, 115], black-box models [116, 117], biomechanical models [118, 119] or non-linear polynomial models [120, 121].

2.5 Muscle Synergy

The central nervous system (CNS) coordinates and controls the numerous DOFs of the musculoskeletal structure, and is capable of dexterously performing a wide variety of motor tasks. The relationship between the input muscle activations and the output at the joint (in terms of both position and force) is quite complicated and highly non-linear [84, 31]. Even though, this leads to an infinite set of solutions to choose from, the CNS is still capable of performing the motor tasks efficiently and rapidly [60]. It has long been hypothesized that the CNS uses a modular approach to

Figure 2.6: Time-varying synergies model. In this simulated example, two time-varying synergies (a) are scaled in amplitude and shifted in time (b), and then combined to construct two different patterns (c). (a) The rows in each synergy (W_1 and W_2) represent the activation time courses of the three muscles (m_1 to m_3), with the amplitude, shown in color code, normalized within each synergy to the value of the maximum sample. The profile in the box below each synergy represents the time course of the synergy averaged across muscles. (b) To generate a specific muscle pattern, every muscle in each synergy is first scaled in amplitude by a non-negative coefficient (c_1 in the illustration representing the time course of the three muscles of W_1) and shifted in time by an onset delay (t_1). The three curves in a box represent W_1 before (dashed traces) and after (solid traces) scaling and shifting. (c) The elements of the first synergy (magenta shaded area) are then summed together with corresponding elements of the second synergy (green shaded area) to generate the complete pattern (solid line). In this illustration, the amplitude coefficients (c_1 and c_2) are represented as the height of the rectangle below the muscle patterns, and the onset delays (t_1 and t_2) are represented by the horizontal position of the left edge of the rectangle. [4].

encapsulate a set of input commands in a module; these modules are then flexibly combined to generate the inputs required to control a motion task. This modularity is generally referred to as muscle synergies in the context of muscle activity space, and are defined as a coordinated activations of a group of muscles; evidence of its existence have been observed in the case of many species [122, 123]. A set of synergies are then linearly combined to generate the entire set of muscle activity patterns necessary for performing a particular task. Synergistic activation of muscles can help in

simplifying dimensionality of control and reduce computational cost, thereby making it easier for the CNS to control the activities of the numerous muscles in the body and produce a coordinated motion of the skeletal structure. However, reduced dimensionality of control leads to restriction in the possible input muscle activation space, and thereby capable of producing only a limited set of output motor tasks [5]. In the work by D'Avella et al [4], the authors analyzed the muscle activation patterns of thirteen hind muscles in four intact and unrestrained frogs during kicking motion after cutaneous stimulation of the foot. They identified a single set of time-varying muscle synergies from the entire muscle activity patterns by performing a decomposition algorithm involving a particular optimization criteria. This small number of muscle synergies was responsible for producing the entire repertoire of kicking movements in the frogs and Fig.2.6 represents a simulation of the time-varying synergy for better understanding of the concept.

There are broadly two types of synergy models according to the work published by Alessandro et al. [5]:

1. **Temporal and Synchronous Synergies:** In these models, the control input is defined as a linear combination of k vectors $\mathbf{w} \in \mathbb{R}^m$, with one-dimensional time-varying coefficients $a(t) : \mathbb{R}^+ \rightarrow \mathbb{R}$ (Figure 2.7 A):

$$\mathbf{u}(t) = \sum_{j=1}^k a_j(t) \mathbf{w}_j \quad (2.2)$$

Each vector $\mathbf{w}_j$ specifies a weighted distribution of the input variables, and its coefficient $a_j(t)$, and determines its temporal evolution. In the case of *temporal synergy model*, the coefficients $a_j(t)$ serve as the task-independent predefined modules, and the vectors $\mathbf{w}_j$ represent the new (task-dependent) control input. This results in reducing the control space to k m-dimensional vectors, and thus synergies are interpreted as the temporal patterns that are recruited selectively by different muscles.

In contrast, the *synchronous synergy model* defines the task-independent synergies as the vectors $\mathbf{w}_j$. The new control input $a_j(t)$ belongs to the infinite

Figure 2.7: Different models of muscle synergies: (A) The temporal and the synchronous models explain motor signals as linear combinations of muscle balance vectors (spatial patterns), with 1-dimensional time-varying coefficients. In the temporal model, these coefficients act as task-independent predefined modules, and the spatial patterns as the new (task-dependent) control input. On the other hand, in the case of synchronous model, the control input is represented by the temporal patterns, while the spatial patterns act as predefined modules. (B) Time-varying synergies are spatio-temporal predefined motor patterns, which can be scaled in amplitude and shifted in time by the new input coefficients [5].

dimensional space of the one-dimensional real functions. Synchronous synergies are co-varying group of muscles, and are also called time-invariant synergies, spatially fixed muscle synergies, or muscle modes.

2. **Time-varying synergy:** This model defines the control input as the superposition of k task-independent vector-valued function $\mathbf{w}_t : \mathbb{R}^+ \rightarrow$ (Figure 2.7 B):

$$\mathbf{u}(t) = \sum_{j=1}^k a_j \mathbf{w}_j(t - \tau_j) \quad (2.3)$$

Each synergy $\mathbf{w}_j$ can be scaled in amplitude and shifted in time by means of the coefficients $a_j, \tau_j \in \mathbb{R}$. These coefficients represents the new control input, and have to be chosen in order to accomplish the task. Thus, this results in reducing the input-space to a $2 \times k$ dimensional space. From a neuroscientific perspective, these synergies are genuine spatio-temporal muscle patterns which do not make any explicit spatial and temporal separation.

Linear dimensionality reduction techniques are used to transform EMG signals from a high dimensional muscle activity space, to a low dimensional synergy space [124]. The choice of the feature projection algorithm is mainly dependent on the type of constraints set in decomposing the original EMG data. These algorithms extract synergy features by looking into the EMG data collectively to identify muscle coordination patterns in performing a motion-task. Some of the commonly used decomposition algorithms are as follows

1. **Non-negative matrix factorization (NMF):** It is the commonly used technique for extracting time-invariant muscle synergies and has relaxed constraints on orthogonality and statistical independence of the principal synergy components [33]. The specialty of this algorithm is that it generates only positive valued entities in the synergy extraction, which is similar to the pull-only behavior of the muscles. It is also one of the widely used algorithms to perform simultaneous and proportional decoding of two or three DOFs, by linearly mixing the synergy components corresponding to each DOF.
2. **Principal component analysis (PCA):** This algorithm generates orthonormal synergy components, aiming at maximizing the variances in the data-set, and is one of the widely used method for data compression. In the work by Artemiadis et al [125], they used PCA to reduce the dimensionality of the both the

input space as well as the output space in order to simplify the relationship between the EMG signals and the corresponding joint positions, and produce better decoding results.

3. **Independent component analysis (ICA):** It produces statistically independent synergy features from multiple EMG signals [126], thus assuming that synergies represent distinct information sources. They are generally used to identify subject-independent synergies aimed at eliminating cross-talk and other interfering signals.
4. **Linear discriminant analysis (LDA):** This algorithm is a supervised technique aimed at producing task-specific synergies, by maximizing between-class variance and minimizing within-class variance. They are quite useful in building decoding models for discriminating between different types of movements or gestures [127, 88].

2.6 Minimum-Jerk Trajectory

Neville Hogan [128] noted that smoothness can be quantified as a function of jerk, which is the time derivative of acceleration. Hence, jerk is the third time derivative of location (i.e., position). If the location of a system is specified by variable $x(t)$, then the jerk of that system is:

$$jerk \ddot{x}(t) = \frac{d^3 x(t)}{dt^3} \quad (2.4)$$

For the central nervous system to move our hand or some other end effector smoothly from one point to another, it may minimize the sum of the squared jerk along its trajectory. For a particular trajectory $x_1(t)$ that starts at time t_i and ends at time t_f , the smoothness is measured by calculating a jerk cost:

$$\int_{t=t_i}^{t_f} \ddot{x}_1(t)^2 dt \quad (2.5)$$

Note that jerk cost is a scalar; the expression above assigns a number to the function

$x_1(t)$. A function $x(t)$, among all possible functions, which smoothly connects a starting point to a target in a given amount of time has the minimum jerk cost.

To make the issue concrete, lets imagine the scenario where we need to move an object d units in a t second period. The object will be at rest at start time and at the end of the movement. This can be written as:

$$\text{Properties of } x(t) : \left\{ \begin{array}{ll} x(0) = 0 & x(t) = d \\ \dot{x}(0) = 0 & \dot{x}(t) = 0 \\ \ddot{x}(0) = 0 & \ddot{x}(t) = 0 \end{array} \right\} \quad (2.6)$$

In order to find the trajectory $x(t)$ which has the smoothest path, we need to assign a jerk cost to each possible trajectory, and find the trajectory with the least cost. Mathematically, this calculation corresponds to minimizing the functional:

$$H(x(t)) = \frac{1}{2} \int_{t=0}^t \ddot{x}^2 dt \quad (2.7)$$

The function $x(t)$ that happens to have its sixth derivative equal to zero will minimize the jerk function. The differential equation $x^{(6)} = 0$ has the general solution of:

$$x(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \quad (2.8)$$

with derivatives:

$$\begin{aligned} \dot{x}(t) &= a_1 + 2a_2 t + 3a_3 t^2 + 4a_4 t^3 + 5a_5 t^4 \\ \ddot{x}(t) &= 2a_2 + 6a_3 t + 12a_4 t^2 + 20a_5 t^3 \end{aligned} \quad (2.9)$$

All that is needed now is to determine the six constants a_0 to a_5 The first 3 constants can be determined from the initial conditions. For $t = 0$

$$\begin{aligned} a_0 &= x(0) \\ a_1 &= \dot{x}(0) \\ a_2 &= \frac{1}{2} \ddot{x}(0) \end{aligned} \quad (2.10)$$

The last 3 constants can be derived from the terminal conditions

$$\begin{aligned}
x(t) &= a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \\
\dot{x}(t) &= a_1 + 2a_2 t + 3a_3 t^2 + 4a_4 t^3 + 5a_5 t^4 \\
\ddot{x}(t) &= 2a_2 + 6a_3 t + 12a_4 t^2 + 20a_5 t^3
\end{aligned} \tag{2.11}$$

In matrix form

$$\begin{bmatrix} x(t) - a_0 - a_1 - a_2 \\ \dot{x}(t) - a_1 - 2a_2 \\ \ddot{x}(t) - 2a_2 \end{bmatrix} = \begin{bmatrix} t^3 & t^4 & t^5 \\ 3t^2 & 4t^4 & 5t^5 \\ 6t & 12t^2 & 20t^3 \end{bmatrix} \begin{bmatrix} a_3 \\ a_4 \\ a_5 \end{bmatrix} \tag{2.12}$$

Then,

$$\begin{bmatrix} a_3 \\ a_4 \\ a_5 \end{bmatrix} = \begin{bmatrix} t^3 & t^4 & t^5 \\ 3t^2 & 4t^4 & 5t^5 \\ 6t & 12t^2 & 20t^3 \end{bmatrix}^{-1} \begin{bmatrix} x(t) - a_0 - a_1 - a_2 \\ \dot{x}(t) - a_1 - 2a_2 \\ \ddot{x}(t) - 2a_2 \end{bmatrix} \tag{2.13}$$

Once the parameters are known, the entire trajectory from start time 0 to terminal time t is determined as

$$x(t) = \sum_{k=0}^5 a_k t^k \tag{2.14}$$

Chapter 3

Role of Muscle Synergies in Real-Time Control of Upper Limb Motions

3.1 Introduction

Myoelectric signals provide information like the intent and extent of motion, simplified synergistic model of motion control, and on biomechanics at the joint level as the impedance characteristics. As much as they offer useful information, they are also challenging to use in motion control, due to the fact that electromyographic (EMG) signals are variable, and are subjected to degradation due to change in skin conductivity i.e. sweat, muscle fatigue and shift in electrode position [31]. The two important factors detrimental to the performance of any decoding algorithm are: the feature extraction techniques applied, and the learning algorithm used to build the decoder relating the input (EMG signals) to the corresponding output (control-motions).

Feature extraction techniques are used to characterize the EMG signals and extract useful information, in order to be able to interpret them better. Two main approaches are the most widely used (Ison et al. [35]): a first one named *EMG features* relying on structural characteristics from each individual EMG channel (like time-domain, frequency-domain, time-frequency domain characteristics [34, 129]), and a second one namely known as *synergy features* which uses information from multiple EMG

signals. Time-domain features are computationally simple to evaluate [130], and provide good levels of decoding accuracy, whereas frequency and time-frequency domain analyses foresee a higher computational process and furthermore they do not significantly increase the decoding accuracy when compared with the previously mentioned features [75]. *Synergy features* extract coordination patterns across multiple EMG channels, by means of time-variant or time-invariant synergies [131, 124]. Muscle-synergy is hypothesized to be the method by which brain simplifies motor control, and synergistic muscle activation patterns have been observed while performing specific movements, e.g. reaching tasks [40]. These features showed to be robust and not sensitive to amplitude cancellations, and also help control strategy simplification by reducing the control dimensionality [39]. Furthermore, synergy features have shown to be consistent and robust to slight shift in electrode position [33].

Apart from feature extraction techniques, the type and amount of training data used also does affect the performance of the decoder. Incorporating dynamically varying data [132] and including multiple limb positions [133] have shown to improve decoding performance, but causes an increase in the training data-set and ultimately leading to higher computational burden. Learning algorithms like artificial neural networks (ANN), linear discriminant analysis (LDA), support vector machines (SVM), and Gaussian mixture models have been extensively used in myoelectric-based motion control, and they provided good levels of accuracy. Nonetheless the learning efficiency and rate of classification should be fast enough for effective utilization in real-time applications [34]. Extreme learning machine (ELM) is a relatively new supervised learning algorithm and represents a single-hidden layer feed-forward neural network (SLFNN) [134]. The learning rates are significantly higher than the traditional back-propagation based learning machines, and it provides an efficient solution to generalized feed-forward networks. ELM offers faster rates of training, less degree of intervention and ease of implementation. Shi et al. [36] shows that the running time of ELM is much faster than LDA and SVM; also, the results indicate the classification accuracy of ELM is overall higher than LDA, and almost comparable with that of SVM, thus showing the potential of ELM for real-time myoelectric con-

trol of assistive devices.

3.1.1 Aim

The main focus of this study is to compare and contrast the performance of ELM using the two approaches *EMG features* (more specifically time-domain features) and *Synergy features*; this study will focus on the differences between the two approach in decoding shoulder and elbow motions. Decoding strategies could be either regression or classification: regression based decoding strategies are mostly employed in controlling devices, which are mainly aimed at augmenting the capability in either healthy or weak subjects, by amplifying human force/torque [135, 136]. In some cases, a neuromusculoskeletal model is used to relate EMG signals to torques produced at the joints, and the level of assistance to be provided by the device is set using a scaling factor [137, 138]. In this case we will focus on a classification model, since the target population is intended to be patients affected by brain injury with specific focus on stroke. In this kind of subjects, the use of regression models is particularly challenging due to the degraded EMG activity, with a resulting acquired signals often hard to interpret and uncontrolled muscular co-contractions (hypertonia) leading to unwanted torques generated by the device [135]. Hence we opted for an approach based on detection of a preset number of movements (classes) [139] where the decoder is devoted to classify the movements in real-time and control a graphical user interface replicating a human limb. Our hypothesis is that *synergy-features* could provide a more reliable and robust means of decoding myoelectric signals, and if proven initially in the case of healthy subjects, might translate reasonably to stroke population. Though, synergies of healthy and stroke population can be completely different, sufficient evidence exists regarding the existence of synergies (either intact or modified) which are consistent in the case of stroke patients [140]. This could potentially enable the use of a decoding algorithm using *synergy-features* for building a reliable human-machine interface to provide rehabilitation or assistance. This study however lacks the testing with stroke patients due to constraints regarding time and ethical matters associated with stroke-based testing.

While ELM has been applied to determine performance measures in an offline con-

text [36], we want to extend the experiment to online decoding, and determine how accurate ELM can fare in real-time control of assistive devices. To our knowledge, no previous work has employed ELM to test the performance of the decoder for myoelectric control in an online scenario. In order to perform online decoding, a virtual avatar replicating a human limb has been implemented, and it enables a number of movement classes comprising shoulder and elbow degrees of freedom. The acquired EMG signals are processed in real-time, the classified outputs actuate the virtual avatar to provide feedback to the user, and enables modification of user learning to improve the performance, and understand the inverse model of the decoder to better control the graphical interface. The main target is to implement the algorithm and be able to interface a soft wearable exosuit for the upper-limb that is being currently developed in the lab.

The results presented in this chapter can be found in [141].

3.2 Methods

3.2.1 Subjects

A total of 7 healthy subjects (6 males and 1 female, age 26.85 ± 1.57 years) participated in the experiment, and they all provided written informed consents. The procedures were approved by the Institutional Review Board at Nanyang Technological University.

3.2.2 Experimental Setup

The setup includes Wireless Electromyographic system (Trigno wireless, Delsys Inc.), which is used to record the surface EMG signals. The Trigno EMG sensors employ a proprietary four silver bar contacts for detecting EMG signal at the skin surface (<https://www.delsys.com/>). A real-time Data acquisition board (Quanser QPIDe) is used to acquire the EMG signals as analog inputs, and the acquisition frequency has been set to 1 kHz. A MATLAB/Simulink based custom program is then used to interface the myoelectric signals, processing them and running the classification al-

gorithm. A high level routine converts the decoder output into control signals to a simulated arm in the virtual environment, thereby providing visual feedback to the subject during the *testing phase*.

Figure 3.1: **Training and Testing phase:** a) Represents the **offline training phase**, where the graphical user interface instructs the subject to perform specific movements for specific period of time. The EMG data is then used to build the decoding model which is specific for each subject. b) The **online testing phase**, where EMG signals are decoded in real-time, and facilitates the movement of the virtual avatar.

3.2.3 Experimental Protocol

The investigation was divided into two experiments, and executed on two different days. Each experiment included two phases: a *training* and a *testing* phase respectively. **Experiment 1** was performed using *EMG features*, while **experiment 2** using *synergy feature*. Figure 3.1 shows the phases of the *training phase* as well as the online *testing phase*. EMG signals were recorded by seven channels and electrodes were placed on the muscles mainly responsible for execution of the shoulder and elbow movements involved, and are as shown in figure 3.2. The skin preparation and electrode placement on the various muscles were followed according to the protocol mentioned in the SENIAM repository [142]. The five different *motion-classes* involved in the experiment are as shown in figure 3.3.

During the *training phase*, subjects were instructed to perform all the *motion classes* and each of them is repeated ten times, for a total fifty repetitions; in this phase the main purpose is to acquire the EMG signal corresponding to the different movement

Figure 3.2: **Muscles and electrode placement:** Illustrates the muscles utilized in the experiment and the respective electrode placement on the muscles.

classes. A graphical user interface indicates the movement (class) to be performed (trial) with two seconds of rest between two consecutive movement trials (each 3 seconds). A ten seconds resting phase is provided upon completion of ten repetitions for the same class. The EMG signals acquired during the *training phase* are used to train the decoder for the successive online *testing phase*.

During the *testing phase*, the subject's EMG activity is detected and used to tele-operate a virtual avatar in the graphical user interface: the purpose is to allow the subject to learn the inverse model of the decoder and control the virtual model: in a scenario where an assistive device is used, the virtual avatar is intended to be a training interface before the user wears the device itself. The graphical interface provides the instruction by indicating the name of the class; subjects were requested to move their arm in such a way the decoder classifies the movement and reproduce it on the simulated avatar. The users were allowed to see their arm in addition to the visual feedback provided by the avatar. Each *motion-class* is performed twenty times, and the instructions are provided in a randomly generated sequence. Each trial is considered to be completed upon successful transition of the virtual arm, from the rest pose to the respective *motion-class* indicated, and holding the position for 0.5 seconds. There is no time restriction in completing the task, and a trial is considered

successfully completed when the virtual movement matched the one requested.

Figure 3.3: **Motion-classes:** The five different motion-class and the rest pose which represents the sixth class. The movement starts from the rest pose and transitions to the target pose as indicated in the figure, and motion is designed to follow a minimum-jerk trajectory.

The avatar consists of a human upper body where the shoulder and elbow joints can be actuated. The shoulder joint includes the actuation of the flexion/extension and the abduction/adduction motions, whereas the elbow joint includes that of the flexion/extension motion. These three above-mentioned joint variables control the motion of the avatar and can achieve the various target postures required for this experiment. The avatar is designed to stay at the initial or rest configuration (as indicated by the rest class in figure 3.3) when the user is relaxing. The transition from one posture to another posture is governed using the minimum-jerk criteria [128], whereby it generates a smooth bell-shaped velocity profile from the current joint position to the target joint position, in a specified amount of time. Minimum-jerk trajectory profiles are similar in nature to the way our brain controls the movement of the limbs from position to another, and hence meant to provide a realistic feedback of the avatar's upper-limb motion, to the user. The time-period for the movement-transition is governed by the maximum value of the absolute differences in each of

the three variables between the current and the target joint positions. A conversion ratio of 1.5 seconds per 90 degrees of motion is defined to obtain the time-period, which is then used to calculate the motion profiles for all the three joint variables starting from the current configuration of joint positions to the target configuration. For example, consider the case where the user is at the rest configuration, and is requested to perform the shoulder flexion motion. As soon as the user starts to perform the shoulder flexion motion, the EMG electrodes capture the activity patterns, and the decoder starts predicting the motion in real-time at each time step. If the prediction is correct the algorithm generates the minimum-jerk motion profile starting from the rest configuration to the target shoulder flexion configuration, and the avatar instantaneously follows the prescribed trajectory. However, the efficacy of this transition is subject to the constraint that the decoder predicts the desired motion at each time-step throughout the entire time-period of motion from the initial to the target configuration. If for instance, the decoder starts erroneously predicting the incorrect motion-class, a new set of trajectory profiles are generated from the current joint position to the incorrectly predicted target configuration. The experiment is designed such that the decoder predicts the rest motion-class when the user is relaxing, meaning that the EMG activities are below a pre-defined threshold value. Therefore, the avatar always transitions back and stays at the rest configuration, from any joint configuration when the user starts relaxing his muscles.

3.2.4 Feature Extraction

Pre-processing of EMG signals: All the EMG signals are rectified by taking the absolute value, followed by low-pass filtering to remove the high-frequency noise from the signals, resulting in a smooth envelope of the signal. Low-pass filtering is performed using a second-order Butterworth filter, with a cut-off frequency of 10 Hz.

Experiment 1 involves usage of *EMG features*, whereas **experiment 2** uses *synergy features*, for online control of the graphical user interface. The input signals are represented by $X \in \mathbb{R}^{p \times q}$, where p and q are the number of original dimensions (number of EMG channels) and the number of data samples respectively. The features used are as mentioned below.

EMG features: We considered two time-domain features to extract information from the EMG signals [143], with a sliding window of 100 samples (100 ms) and an overlap of 90 samples between two windows to account for processing time: which means an output is produced every 10 ms.

Mean Absolute Value (MAV): It is evaluated by taking the average of each EMG signal in the window frame, providing information on movement duration and effort [144].

$$MAV = \frac{1}{N} \sum_{n=1}^N |x_n| \quad (3.1)$$

where $N = 100$ is the number of samples in the sliding window.

Variance (VAR): It is a measure of the EMG variability, and is an indicator of the EMG signal power and helps in identifying movement onset and contraction [144].

$$VAR = \frac{1}{N-1} \sum_{n=1}^N |x_n|^2 \quad (3.2)$$

For each of the seven EMG channels, these two set of features are extracted, and hence the dimensionality of the input signals become fourteen. The input matrix after the *EMG features* extraction procedures, is represented by $Y_{EMG} \in \mathbb{R}^{2p \times q}$, where p represents the number of EMG channels and q the number of data samples. In this experiment we use seven EMG electrodes (placed on various muscles as mentioned earlier) and therefore, the output of the *EMG feature* extraction is a fourteen-dimensional vector at each time-step.

Synergy feature: These are features which analyze the EMG signals collectively and helps in simplifying the dimensionality of control, potentially reducing the computational cost. There are a variety of dimensionality reduction techniques used in literature, but the widely-used technique for extracting synergistic muscle-activity patterns is the non-negative matrix factorization (NMF). The main advantage of using NMF algorithm is that it has relaxed constraints on orthogonality and statistical independence of the principal synergy components and restricts the activation coefficient to be a non-negative value, which reflects the reality of the neural and muscle activation (pull-only behavior). Any non-negative matrix $X \in \mathbb{R}^{p \times q}$ is decomposed into two non-negative factors $A \in \mathbb{R}^{p \times k}$ and $Y \in \mathbb{R}^{k \times q}$, where p, q and k are the number

of EMG channels, number of data samples, and the number of reduced dimensions respectively. The relation is given by

$$X = AY + E \quad (3.3)$$

$$\begin{bmatrix} x_{11} & \cdot & x_{1q} \\ \cdot & \cdot & \cdot \\ x_{p1} & \cdot & x_{pq} \end{bmatrix} = \begin{bmatrix} a_{11} & \cdot & a_{1k} \\ \cdot & \cdot & \cdot \\ a_{p1} & \cdot & a_{pk} \end{bmatrix} \begin{bmatrix} y_{11} & \cdot & y_{1q} \\ \cdot & \cdot & \cdot \\ y_{k1} & \cdot & y_{kq} \end{bmatrix} + \begin{bmatrix} e_{11} & \cdot & e_{1q} \\ \cdot & \cdot & \cdot \\ e_{p1} & \cdot & e_{pq} \end{bmatrix}$$

where E is the error or residual. Each column in the matrix X represents multi-variate data points. A is the *basis matrix* containing the basis vectors of the synergy space, and Y is called the *coefficient matrix* containing the activation coefficients. The optimization technique used to converge to a stationary point is based on the *non-negative least squares* method proposed in [145]. The number of basis vectors or synergies is chosen based on the explained variance of the data or by the residual error E obtained by approximation. In this experiment, the number of basis/synergy vectors to be used is based on two criteria: firstly, to ensure that at least 90% of the variance in the data could be represented using the reduced dimension and secondly, the point in the cumulative explained variance plot where the change in slope is less than 5% of the variance.

During the *training phase*, the input matrix (*synergy feature*) obtained after performing the decomposition algorithm is represented by the *coefficient matrix* $Y_{SYN} \in \mathbb{R}^{k \times q}$, where k and q are as mentioned above. During the *testing phase*, the *coefficient matrix* are obtained in real time by using the following relation.

$$Y_{SYN} = A^{-1} \times X \quad (3.4)$$

$$\begin{bmatrix} y_{11}^1 & \cdot & y_{1q}^1 \\ \cdot & \cdot & \cdot \\ y_{k1}^1 & \cdot & y_{kq}^1 \end{bmatrix} = \begin{bmatrix} a_{11}^{-1} & \cdot & a_{1p}^{-1} \\ \cdot & \cdot & \cdot \\ a_{k1}^{-1} & \cdot & a_{kp}^{-1} \end{bmatrix} \begin{bmatrix} x_{11} & \cdot & x_{1q} \\ \cdot & \cdot & \cdot \\ x_{p1} & \cdot & x_{pq} \end{bmatrix}$$

where $X \in \mathbb{R}^{p \times q}$ represents the multi-variate data points, $A \in \mathbb{R}^{p \times k}$ represents the *basis matrix* obtained during the *training phase*, and $Y_{SYN} \in \mathbb{R}^{k \times q}$ represents the input matrix after performing synergy-space feature extraction. Therefore, the output

of the *synergy-feature* extraction is k -dimensional vector at each time-step, where k is the number of reduced dimensional space.

3.2.5 Machine Learning Algorithm

We decided to use Extreme Learning Machine (ELM) for decoding the motion classes and consequently controlling the virtual arm model. ELM is an emerging learning paradigm that represents an efficient unified solution to generalized feed-forward neural networks including (but not limited to) single-/multi-hidden-layer neural networks, radial basis function networks, and kernel learning. ELM offers significant advantages such as fast learning speed, ease of implementation, and minimal human intervention [146]. It thus has strong potential as a viable alternative technique for large-scale computing in many different applications, including image [147], text [148], speech [149] and multimodal [150] processing, but also cognitive learning [151] and reasoning [152].

The ELM model [153] implements a single-hidden layer feedforward neural network (SLFNN) with N mapping neurons. The function connecting the input layer with the hidden layer can be expressed as follows, for each neuron $j \in \{1, \dots, N\}$:

$$h_j(\mathbf{Y}) = a(\mathbf{Y}, R_j) \quad (3.5)$$

, where $\mathbf{Y} \in \mathbb{R}^Z$ is an input stimulus which is either Y_{EMG} or Y_{syn} depending on the type of feature used for the experiment , $a(\mathbf{Y}, R)$ is a nonlinear piece-wise continuous function (activation function), characterized by R which denotes the set of parameters of the mapping function. Every j -th neuron has its set of parameters R_j .

The overall output function connecting the hidden and the output layer is expressed as

$$f(\mathbf{Y}) = \sum_{j=1}^N \mathbf{w}_j h_j(\mathbf{Y}) \quad (3.6)$$

, where $\mathbf{w}_j$ denotes the weight that connects the j -th neuron with the output.

The peculiar aspect of ELM is that the parameters R_j are set randomly. Hence, if one uses, for example, Radial Basis Functions to implement $a(.)$:

$$a(\mathbf{Y}, R) = \exp(-\zeta \|\mathbf{Y} - \mathbf{c}\|^2) \quad (3.7)$$

the parameters to be set randomly are the coordinates of each centroid, $\mathbf{c} \in \mathbb{R}^Z$, and the quantity ζ . In this study triangular basis function was used as the activation function.

Accordingly, the hidden layer implements an explicit mapping of the original input space into a new space $\mathbb{R}^N$. Hence, training ELMs is equivalent to solving a regularized least squares problem in a linear space. Let $H \in \mathbb{R}^{n \times N}$ be an activation matrix such that the entry $H_{i,j}$ is the activation value of the j -th hidden neuron for the i -th input pattern. Then, the training problem reduces to the minimization of the convex cost:

$$\mathbf{w}^* = \underset{\mathbf{w}}{\operatorname{argmin}} \|H\mathbf{w} - \mathbf{o}\|^2 + \lambda \|\mathbf{w}\|^2 \quad (3.8)$$

, where λ controls the contribution of the regularization factor.

The vector of weights $\mathbf{w}^*$ is then obtained as follows:

$$\mathbf{w}^* = (H^T H + \lambda I)^{-1} H^T \mathbf{o} \quad (3.9)$$

where $I \in \mathbb{R}^{N \times N}$ is an identity matrix.

The ELM model can be conveniently described as a 2-stage learning machine. In the first stage, the data originally lying in the Z -dimensional space are remapped into a new N -dimensional space (ELM feature space) by exploiting as many ‘random’ neurons. Then, an RLS problem is solved for learning the linear classifier in the N -dimensional space.

The final decision function of ELM for a binary classification problem is:

$$f_L(\mathbf{Y}) = \operatorname{sign}(f(\mathbf{Y})) \quad (3.10)$$

For multiclass problems, it is possible to set multi-output nodes: therefore, m -class classifiers have m output nodes. If the original class label is c , the expected output vector of the m output nodes for the i -th input pattern is $\mathbf{o}_i = [0, \dots, 0, 1, 0, \dots, 0]^T$, with

the c^{th} element of $o_i = [o_{i1}, \dots, o_{im}]^T$ set to one, while the rest of the elements are set to zero.

The classification problem for ELM with multi-output nodes can be formulated as:

$$\min_w \left\{ \frac{1}{2} \|\mathbf{w}\|^2 + C \frac{1}{2} \sum_{i=1}^n \|\epsilon_i\|^2 \right\} \quad (3.11)$$

Subject to: $h(\mathbf{Y}_i)\mathbf{w} = o_i^T - \epsilon_i^T \quad i = 1, \dots, n$

Where $\epsilon_i = [\epsilon_{i1}, \dots, \epsilon_{im}]^T$ is the training error vector of the m output nodes with respect to the training sample $\mathbf{Y}_i$.

Therefore, the binary classification problem can be considered as a specific case of multi-output nodes when m is set equal to one. For both cases, the hidden layer matrix H remains the same, and the size of H is only decided by the number of training samples n and the number of hidden nodes N , which is irrelevant to the number of output nodes (number of classes) m .

3.2.6 Performance Metrics

In order to compare the accuracy of the ELM algorithm for *EMG features* and *synergy feature*, we evaluate the *offline performance* (corresponding to the *training phase*) and *online performance* (corresponding to the *testing phase*).

Offline Performance is defined as the accuracy of the decoder to classify the EMG patterns and associate them to the correct *motion-class*. The quantity of data samples collected during the training phase is split in two parts: training data-set which is used to train the decoder and its neural network, and the testing data-set which is used to test the performance of the decoder in predicting the *motion-classes*. A 2-fold cross validation procedure is used to determine the number of hidden layer neurons, and avoid over-fitting of the data. The testing data-set is used to determine the classification accuracy once the model parameters are optimized according to the following equations:

$$Acc_{off} = \frac{n_c}{n_c + n_w} \times 100(\%) \quad (3.12)$$

where n_c and n_w represents the number of correctly and wrongly classified samples

respectively, from the testing data-set.

Online performance: It has the purpose of quantifying the accuracy of the algorithm during the online testing phase, where the subject is controlling the virtual arm by EMG signals and three of the indicators are based on the work by Li et al.[154] which are described below.

Figure 3.4: **Performance metrics:** Evaluation of the different metrics for a typical trial. An example of shoulder protraction trial is indicated in this figure in order to explain each metric. Subjects, starting from the rest position, are instructed by a message on the screen to execute a shoulder protraction. Movement onset initiates when decoder starts predicting the *motion-classes*. *Motion selection time* is defined as the interval between movement onset and decoder output which corresponds to the desired *motion-class*. *Motion completion time* is the time duration between movement onset and the final configuration of the virtual arm corresponding to the requested movement. *Classification accuracy* is the decoding accuracy throughout the trial.

1. **Motion Selection Time:** It is the amount of time needed by the decoder to decode the human EMG patterns, translate them into motor commands to the virtual arm. It is mainly the time needed by the decoder to identify the desired *motion-class*.
2. **Motion Completion Time:** This is the amount of time subjects take to utilize

their EMG signals and move the virtual arm into the desired position, and holding it for 0.5 seconds.

3. **Learning Trend:** It provides the trend of *motion completion time* through the experiment for each *motion-class*. The decreasing slope of the exponential fitting indicates a positive learning rate, provided by the general formula:

$$y(x) = a \times e^{-bx} + c \quad (3.13)$$

where $x \in \{1, 2, \dots, 20\}$ is the number of repetitions, y is the time taken to complete the task (a particular *motion class*) corresponding to x . While a, b, c respectively represent the initial performance, the learning rate, and the steady state value.

4. **Online Classification Accuracy:** It is used to calculate the classification accuracy of the decoder for each class. It is the ratio between the number of samples from the decoder matching the desired motion class and the total number of samples for that particular trial. Classification accuracy is calculated as:

$$Acc_{on} = \frac{1}{N} \sum_{i=1}^N \frac{n_i}{n_i + m_i} \times 100(\%) \quad (3.14)$$

where N represents the number of successfully completed trials in a particular *motion-class* for a subject. n_i and m_i represents the number of correctly and incorrectly classified samples respectively in a single trial i .

5. **Variability in muscle activity trends:** This is evaluated for each subject and for each *motion-class*, across all the seven EMG channels for both *EMG feature* and *synergy features*. It is the mean of the standard deviation values of the EMG activity across all EMG channels during the 20 repetitions of each *motion-class*. Each trial or repetition is normalized with respect to the completion time to indicate percentage of motion and resampled to a common set of 200 samples. The mean muscle activity and the deviation from the mean are calculated at each instant during the entire motion. It provides insight into the strategy used

by the subjects and the performance consistency (precision) across the whole experiment and hence, the decoder performance.

$$Variability = \frac{1}{nEMG} \frac{1}{nSamples} \sum_{i=1}^{nEMG} \sum_{j=1}^{nSamples} \sigma_{ij} \quad (3.15)$$

where $nEMG = 7$ represents the number of EMG channels, $nSamples = 200$ represents the number of samples during each motion after resampling, and σ_{ij} is the standard deviation of the muscle activity for the i^{th} EMG channel and at the j^{th} time sample. The lower the variability value the better the decoder performance.

$$\sigma_{ij} = \sqrt{\frac{1}{nRep} \sum_{k=1}^{nRep} (E_{ij}^k - \mu_{ij})^2} \quad (3.16)$$

where $nRep = 20$ represents the total number of repetitions for each *motion-class*, E_{ij}^k is the EMG activity for the i^{th} EMG channel at the j^{th} time sample and k^{th} repetition, and μ_{ij} is the mean of the EMG activity for the i^{th} EMG channel at the j^{th} time sample.

Figure 3.4 represents the various quantifying measures used for online decoding. A two-way Anova was performed to compare the statistical significance between *EMG features* and *synergy feature* for the five *motion-classes*.

3.3 Results

3.3.1 Decoder Offline Performance

Offline Decoder Classification accuracy has been evaluated for each subject across all the five different motion classes. The average accuracy in **experiment 1** (*EMG features*) resulted in $99.37\% \pm 0.81\%$, whereas the average accuracy in **experiment 2** (*synergy feature*) is $65.73\% \pm 2.60\%$. Based on a validation data-set, it resulted that the optimal number of hidden neurons for **experiment 1** (*EMG features*) was 5000 units;

contrarily 3500 units were chosen for **experiment 2** (*synergy feature*), to avoid over-fitting. The difference in the number of hidden neurons did not affect the processing time significantly during the testing phase. It took an average of 2.87 ± 0.06 seconds to predict the output of 10000 samples in the case of *EMG features*, whereas it took around 2.01 ± 0.02 seconds to predict in the case of *synergy feature*. Therefore, for real-time predictions, the difference in the number of hidden neurons would hardly impact the *motion selection time* or the *motion completion time*, especially because ELM is considered to have a very fast running time. The number of synergy vectors to be used in the experiment is based on two criteria, as mentioned previously. From the initial analysis it was determined that, using the first four synergy vectors matched the requirements, and was fixed for all the subjects to have uniformity. The average residual error obtained for all the subjects had an R^2 value of $5.38\% \pm 3.6\%$.

Figure 3.5: Figures represent a polar plot indicating the mean and standard deviation for all the *motion-classes*, in the case of *EMG* and *synergy* features across all subjects. a) indicates the plot of online classification accuracy, b) indicates the plot of motion selection time, and c) indicates the plot of motion completion time.

3.3.2 Decoder Online Performance

Online Classification Accuracy: The average classification performance of the decoder in the case of **experiment 1** is $84.09 \pm 14.35\%$, whereas in the case of **experiment 2** is $91.79 \pm 9.86\%$. The online classification accuracy reached with the *synergy feature* differs from the one reached with the *EMG features* with high statistical significance (two-way Anova, $F_{1,1284} = 107.81, p < 0.001$), for all the five *motion-classes*.

The classification accuracy for each *motion-class* and for both types of features are as shown in figure 3.5 A. The confusion matrix of the classification accuracy is represented in figure 3.6 and 3.7 corresponding to *EMG features* and *synergy feature* respectively, and help to get a better understanding of the misclassifications in decoding.

Figure 3.6: Normalized confusion matrix across all subjects in **experiment 1** when the decoder uses *EMG features*. This plot gives an idea of the misclassifications happening during decoding. The rows indicate the actual or requested *motion-class*, and the columns indicate the decoder prediction accuracy under each of the *motion-classes*, averaged across all the trials and subjects.

Considering the metrics used to characterize online decoder performance during the *testing phase*, it was found that **Motion Selection Time** for **experiment 1** was 0.15 ± 0.21 seconds, while it was 0.11 ± 0.19 for **experiment 2**. A high significant difference was found between the two types of feature ($F_{1,1284} = 12.428, p = 0.00044$); Anova test revealed a significant interaction between the type of the feature and the *motion-class* ($F_{4,1284} = 14.265, p < 0.001$), in particular for elbow extension and shoulder retraction, the difference between *EMG features* and *synergy feature* did not reach significance (according to a post-hoc Fisher test). The selection time for each *motion-class* and for both types of features are as shown in figure 3.5 B.

For **Motion Completion Time** the average time taken to complete each task across

Figure 3.7: Normalized confusion matrix across all subjects in **experiment 2** when the decoder uses *synergy feature*. This plot gives an idea of the misclassifications happening during decoding. The rows indicate the actual or requested *motion-class*, and the columns indicate the decoder prediction accuracy under each of the *motion-classes*, averaged across all the trials and subjects.

all the subjects and *motion-class*, in **experiment 1** is 3.09 ± 1.98 seconds, whereas it is 2.09 ± 0.30 seconds in **experiment 2**. According to the two-way Anova test, there is a high significant difference ($F_{1,1284} = 101.85, p < 0.001$) between the classification accuracy between the *EMG features* and the *synergy feature*, and the difference is significant for all the five *motion-classes* as observable for 3.5 C.

The **Learning Trend** values have been evaluated for each *motion-class* across all subjects and for both the experiments are as shown in Table 3.1 and 3.2. A negative value indicates the occurrence of learning, leading to an improvement in performance, and contrary for the case when the value is positive. There is no consistent indication for learning trend across subjects and task, meaning that the decoder performance is strictly dependent on the features (EMG vs synergy) used for training and classification.

Variability in muscle activity trends: A typical muscular activation pattern in a subject when performing the shoulder protraction and shoulder retraction movements (multi-articular movements) is shown in figure 3.8. A reduced set of *motion-classes*

Table 3.1: Learning trend. Learning rate values for all the subjects for each of the *motion-class* in **experiment 1** (*EMG features*).

Subject	Elbow Flexion	Elbow Extension	Shoulder Protraction	Shoulder Retraction	Shoulder Flexion
Subject1	-0.0019	0.0023	0.0029	0.0308	0.0150
Subject2	-0.0074	0.0104	-0.0103	0.0233	-0.0150
Subject3	-0.0381	-0.0187	-0.0373	-0.0499	-0.0194
Subject4	0.0061	-0.0090	0.0347	0.0188	0.0101
Subject5	0.0031	-0.0082	-0.0004	-0.0012	0.0138
Subject6	0.0132	0.0096	-0.0010	-0.0047	0.0018
Subject7	-0.0033	0.0034	-0.0045	-0.0170	-0.0075

Table 3.2: Learning trend. Learning rate values for all the subjects for each of the *motion-class* in **experiment 2** (*synergy feature*).

Subject	Elbow Flexion	Elbow Extension	Shoulder Protraction	Shoulder Retraction	Shoulder Flexion
Subject1	-0.0000	0.0036	-0.0066	0.0002	-0.0004
Subject2	-0.0000	-0.0120	0.0002	-0.0006	0.0029
Subject3	-0.0156	0.0023	-0.0027	-0.0010	0.0032
Subject4	-0.0009	0.0046	0.0029	-0.0001	-0.0040
Subject5	-0.0007	0.0098	-0.0007	-0.0009	-0.0029
Subject6	-0.0075	-0.0292	0.0002	-0.0001	-0.0008
Subject7	-0.0046	0.0017	-0.0006	-0.0007	0.0018

are shown for better visual clarity and understanding. It can be observed that the EMG activity is smoother and less variable in the case of *synergy feature* decoded action, than in the case of *EMG features*. The variability values for each subject and for each *motion-class* are as shown in figure 3.9. The values are very high for the shoulder movements in the case of *EMG features* when compared to *synergy feature*, and the trend is pretty much similar for most cases in the elbow movements as well. A possible reason for the aforementioned difference might be in the presence of visual feedback provided to the subject by the virtual avatar, which was present in the testing phase and not in the training one. In the training phase the subjects were instructed to execute a movement and EMG channels were acquired to train the decoders. The testing phase consisted in asking the subject to perform movements corresponding to the selected classes and the results of the decoded movements were promptly shown as the decoded motion of the virtual arm in the visual feedback. There is a

significant difference between the *EMG features* and *synergy feature* decoders in the case of online classification accuracy, with the *synergy feature* decoder performing better and allowing subject to control the virtual arm in a faster way (see motion completion time metric). The difference in online performance between the two decoders may alter considerably the muscular activation pattern by the subjects, who perceive the delay in decoding the desired movements provided by visual feedback. When instructed to move in a particular direction (*motion-class*) the participants can instantaneously perceive the efficacy of the decoder, and in the case of *EMG features* decoding, they tended to adjust by modifying the contraction patterns, and that's why the EMG signals appear to be less smooth and present higher variability than in the case when *synergy feature* decoding was used.

Figure 3.8: Represents the mean and standard deviation plot of the EMG activity for subject 4 in each of the *motion-classes*. The plots in black and red pertain to the EMG activity during testing phase (20 repetitions) corresponding to *EMG features* and *synergy feature* respectively.

Figure 3.9: The mean of the standard deviation values of the muscle activity across all muscles during the entire motion (standard deviation values are as shown in figure 3.8) is indicated for each subject and each *motion-class*, in the case of *EMG features* and *synergy feature*.

3.4 Discussion and Conclusion

In this study our aim was to point out the differences in classification strategy using two approaches for feature extraction procedures. The offline classification accuracy indicated better performance in the case of *EMG features* when compared to the *synergy feature*, whereas one can observe an exact opposite trend in the case of on-

line classification accuracy. This result is in line with other previous contributions showing that there is no correlation between offline and online classification accuracy [155, 156]. The main difference between the offline and online motion decoding is that in the second case, a real-time visual feedback of the user’s performance is provided. Visual feedback plays a very important role in enabling the brain to adapt and learn the dynamics of the system better, thereby improving the efficacy of decoding, which is definitely missing in the offline scenario [30]. Hence, real-time performance metrics are important in order to examine the robustness and reliability of pattern recognition and eventually implement a control strategy able to precisely detect subject motor intention by means of EMG signals [154].

The online classification metrics allowed to quantify the reliability of the decoder’s performance for both EMG and Synergy features and compare them. Based on the results, we observe better decoding accuracy in the case of synergy features when compared to the EMG features. However, some previous study suggests that continual interaction and adaptation due to real-time visual feedback by the user could help improve the decoding accuracy [86]. Another study also showed that subjects are capable of learning the inverse dynamics of the model, regardless of the intuitive nature of the mapping function [157]. The level of intuitiveness of the model and the time taken for familiarization with the decoder, are factors which influence the improvement in decoding performance. In our experiments, each motion-class was performed 20 times by each subject during the online testing, and yet we did not observe a consistent learning trend (Tables 3.1 and 3.2); which means that the optimum level of learning has not been reached yet: relatively to our primary target, which was the comparison between two feature extractions, the absence of a learning trend or adaptation is not detrimental and does not affect the final results. Since the number of repetitions is constant in both the feature types, the absence of subjects adaptation implies that *synergy feature* based decoder is more effective than *EMG features*, and does not require familiarizing time in order to improve the performance; contrarily there might be the possibility that for higher number of trials, the two decoders might converge to the same accuracy level, but still the *synergy feature* based decoder remains the optimal one, especially because it resulted to be more

versatile and efficient in translating user biometric signals into motor command to the simulated virtual environment as reported in the previous sections.

Despite significant better online performance in *synergy feature* than *EMG feature*, there are still some cases in which the two decoders are comparable. Taking a closer look at the classification accuracy in the confusion matrix (fig 3.6 and fig 3.7) between the target class (requested to the subject) and the predicted class (decoded from subject movement) we can observe that the highest percentage of wrong classifications is in the decoding of shoulder protraction movement with a misclassification towards shoulder flexion movements and vice versa. A possible explanation could be found in the similarity between the two movements for what concern the muscular activation sequences during the executions forcing the decoder in misleading the prediction, which gets refined only when the execution has past the movement onset stage. Moreover, we can also notice that *motion-classes* involving shoulder movements have lower classification accuracy than the elbow movements in the case of *EMG features*: this effect is mainly due to the recruitment of multi-articular joints which involves a higher number of muscles compared to single joint (i.e. elbow), and hence the level of uncertainty in decoding increases.

However, in the present study we have not addressed the challenge of simultaneous decoding of multiple *motion-classes* which is recently being explored by Young et al. and Jian et al. [42, 158] on groups of healthy subjects and trans-radial amputees but neurologically intact. Jiang et al. [158], have used synergy based NMF techniques in order to simultaneously control two of the three degrees of freedom at the wrist joint. Contrarily brain damages might hamper our approach because of the resulted abnormal muscular activation and the consequent disruption of synergy formation: it has been found that synergies are either preserved or fractioned in neurologically impaired patients, depending on the extension of the brain lesion and the elapsed time from the stroke onset [140]. Therefore, we believe that extracting synergy information would represent a viable strategy for decoding user intentions even in a simultaneous classification scenario. The main focus of the proposed work was twofold: to highlight the importance of choosing both the extraction features and the decoding algorithm: we demonstrated that *synergy features* and ELM in the context

of myoelectric decoding provided good results and we envision that they might be used in the specific context of assistive technology based on discrete action classification and user intention detection.

Chapter 4

Simultaneous Classification of Movements using Surface Electromyography

4.1 Introduction

4.1.1 Background

Myoelectrically controlled prosthesis and exoskeletons devices aim at closely replicating the natural and efficient motor control strategies of the human [159, 8, 160]. The intention decoding becomes challenging in joints with multiple DOFs (especially distal joints such as wrist and hand which are capable of highly dexterous manipulation), where a single muscle could be responsible for more than one movement [43]. Therefore, decoding user intention can be challenging due to the complex relationship between the muscle activity and the corresponding motions [161]. Furthermore, using surface electromyographic (sEMG) techniques makes it harder to access the activity of the deeper muscle fibers, avoid cross-talk in the signals, and are very sensitive to sweat, fatigue and slight shift in electrode positions [30]. For this reason, pattern recognition techniques using machine learning algorithms have primarily been used in decoding myoelectric signals corresponding to various movements or gestures, and are capable of providing reliable classification accuracies [162, 163].

The main limitation of these strategies is that the decoder can only predict one movement or gesture at a time, lacking the capability to simultaneously classify multiple movements when the user voluntarily performs a combined motion. To overcome this limitation, muscle activities of both the individual and combined movements are also recorded during the calibration phase in order to enhance the capability of the decoder to perform simultaneous classification [91]. Young et al [42] proposed a modified version for simultaneous classification, to enhance the reliability of decoding, but their approach in general is limited by the need for an extensive calibration process which is time consuming.

Various linear and non-linear regression-based algorithms have been proposed for performing simultaneous and proportional decoding of multiple DOFs using surface electromyography [109, 164, 108, 165, 166, 158, 167, 168, 169]. Most of these techniques require a calibration phase where the muscle activities of only the individual movements are recorded; a regression-based algorithm is used to build the relationship between the muscle activity and the desired output (position or force) for each DOF separately, and are then combined in order to predict both individual and combined movements. The decoding strategy proposed by Jiang et al [158] is a widely used method for performing proportional and simultaneous decoding, and involves using non-negative matrix factorization (NMF) to reduce the dimensionality and build the control scheme for each individual DOF.

Alternatively, an approach called linear enhanced training has been proposed by Nowak et. al [170], where the authors built a relationship for the combined movements as a function of the muscle activity of the respective individual movements. The limitation of this approach is that they still needed to record the sEMG signals of both individual and combined movements from a small subset of subjects initially, in order to build the relationship.

4.1.2 Aim

In this chapter, we propose a novel classification algorithm capable of predicting both individual and combined movements by recording the surface EMG data of only the individual motions; More specifically this strategy is implemented without the

need for any prior knowledge of data required to build the relationship between the simple and compound movements as in the study by Nowak et. al [170]. The objective of this study is to test the decoding paradigm in a task involving two DOFs of the wrist and hand movements and evaluate its performance for real-time classification. Another aspect we are interested in exploring, is the use of dimensionality reduction techniques for simplifying control complexity and lowering the computational costs. This could be very beneficial while using an embedded system to enable portability of the processing unit in applications such as prosthesis and exoskeletons.

The results presented in this chapter can be found in [171].

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4.2 Methods

4.2.1 Decoding Model Algorithm

The decoding strategy is designed based on the hypothesis that the features of the combined movement data lie in between the respective base classes [172], and previously shown to be a combination of the data from the respective individual movement [44]. Based on this rationale, we speculate that the muscle activity of the combined movement in a specific low-dimensional space, would lie in the geometrical space enclosed between those of the respective individual movements. Whilst, there are a multitude of dimensionality reduction techniques, we are interested in applying the linear discriminant analysis (LDA) method to project the EMG data to a low-dimensional space, mainly because of the supervised nature of the algorithm, by assigning labels to each movement-class to ensure better discrimination [173]. Whereas, the alternative approaches for data compression, i.e. NMF and PCA are unsupervised techniques and mainly aim at maximizing the variance among the data irrespective of the various movement-classes. The choice of the order of the reduced

dimensional space using LDA is a critical factor in determining the complexity of the algorithm. In case of a two DOF motion-task (two individual movements per DOF), the simplest and least complicated choice, in terms of complexity of algorithm and computational power is a two-dimensional space.

Our proposed strategy involves projecting the original data into a two-dimensional space, where each data point is characterized by a magnitude and an orientation, like in a polar coordinate system. The orientation space for each individual movement-class is defined by an angular boundary (circular sector) which is determined based on the mean and standard deviation of the orientation of the data in each class. More specifically, if the data lies within the two boundaries then it is classified as belonging to that respective movement-class. Whereas, if the data lies outside the boundaries it is classified as a combined movement corresponding to the combination of the individual classes adjacent to it on either side. An ideal representation of the proposed decoding strategy is shown in Figure 4.1. The shaded area in grey represents the data space of the various individual movements of the two DOFs. The area enclosed between the individual classes are the respective combined movements.

However, the validity of this decoding model is dependent on two important criteria:

1. *Orientation constraint*: Data of one agonist/antagonistic DOF pair lies in between the data of the other pair in the orientation space. The decoder loses the ability to predict combined movements in the event when the agonist/antagonistic DOF pair are adjacent to each other.
2. *Linear combination*: The combined movement data lies in the orientation space enclosed by the respective individual movement-classes. This criterion is built on the validity of the first one, which means a violation of the former affects the validity of the latter but not vice versa.

The most important aspect to consider is that the LDA algorithm doesn't impose the *orientation constraint* criterion, which is crucial for the validation of the proposed decoding strategy. Hence, one solution that we propose is to initially project the original data to a three-dimensional space instead of two-dimensional space using LDA. It is worth noting that the two-dimensional projection of the data using LDA, is the

Figure 4.1: A representative figure of the decoding strategy for a two DOF case based on our hypothesis. The EMG data of the individual movement obtained during the calibration phase, when transformed into a specific 2-dimensional space would produce data points as indicated by the shaded region. Based on our rationale, if the data points for the combined movements can be enclosed in the space between the respective individual movements, this strategy could potentially be used to predict both individual and simultaneous motions.

same as projecting the three-dimensional LDA transformed data on the x-y plane. Therefore, instead of performing the default projection (on the x-y plane), we propose to identify an alternate projection of the three-dimensional data which would ensure the validity of the *orientation constraint* criterion.

The original data consisting of individual movements is represented as $X \in \mathbb{R}^{m \times 4N_s}$, where m denotes the number of EMG channels, N_s is the total number of samples in each movement-class, and 4 being the number of individual classes. LDA projects the matrix X into a new matrix $\bar{X}$ given by the relation

$$\bar{X} = AX \quad (4.1)$$

where $A \in \mathbb{R}^{3 \times m}$ is the transformation matrix which projects the data X from an m -dimensional space to a three-dimensional space, and $\bar{X} \in \mathbb{R}^{3 \times 4N_s}$.

The next step is to identify an optimum rotation matrix which will ensure that the two-dimensional projection will meet the *orientation constraint* criterion. The XYX Euler angles convention is used to obtain the rotation matrix (rotation about x axis followed by rotation about y axis, and finally rotation about x axis). The rotation matrix is given by

$$\begin{aligned} \tilde{X}^{ijk} &= \left(R3_x^k \times R2_y^j \times R1_x^i \right) \times \bar{X} \\ i, j, k &\in [0, 5, 10 \dots 180] \end{aligned} \quad (4.2)$$

where $R1_x^i$ is the rotation about x axis by i degrees, $R2_y^j$ is the rotation about y axis by j degrees, $R3_x^k$ is the rotation about x axis by k degrees, and $\tilde{X}^{ijk} \in \mathbb{R}^{3 \times 4N_s}$.

A cost value is defined to evaluate and identify the optimal rotation matrix which will ensure the least overlap between the data of the various movement-classes, and an even distribution of data in the orientation space of the two-dimensional polar plot. The $Var_{between}^{ijk}$ measure is used to identify the projection which will ensure maximum separation between the data clusters of each movement-class. On the other hand, the Var_{within}^{ijk} measure is used to identify the best projection with minimum deviation of data within each movement-class in the orientation space. The cost value for the two-dimensional projection of $\tilde{X}^{ijk}$ which is $\hat{X}^{ijk} \in \mathbb{R}^{2 \times 4N_s}$ is evaluated only if the *orientation constraint* criterion is satisfied. The variance measures are calculated as shown in the equations below,

$$\begin{aligned} Var_{between}^{ijk} &= \sum_{p=1}^M \frac{abs(\sigma^{p-} - \sigma^{p+})}{(\sigma^{p-} + \sigma^{p+})} \\ \sigma^{p-} &= \sqrt{\frac{1}{N_s} \sum_{q=1}^{N_s} (\mu_p - \theta_q^{p-})^2} \\ \sigma^{p+} &= \sqrt{\frac{1}{N_s} \sum_{q=1}^{N_s} (\mu_p - \theta_q^{p+})^2} \end{aligned} \quad (4.3)$$

$$Var_{within}^{ijk} = \sum_{p=1}^M \sqrt{\frac{1}{N_s} \sum_{q=1}^{N_s} (\mu_p - \theta_q^p)^2} \quad (4.4)$$

where, $M = 4$ denotes the number of individual movement-classes, $p+$ and $p-$ represents the adjacent classes, on either side of the individual movement-class p , and μ and σ represent the mean and standard deviation of the orientation θ of the data points in each class p . Each of the variance measures is normalized using the z-score so as to have a common scale for computing the cost value, and the configuration $R3_x^k \times R2_y^j \times R1_x^i$ with the minimum cost value is selected as the optimal rotation matrix.

Once the optimal rotation matrix is determined, the two-dimensional projection of the data (LDA projection followed by optimal rotation) will ensure the validity of the *orientation constraint* criterion in the best possible way. The separation boundaries are fixed to twenty degrees on either side of the mean orientation of the data in each individual movement-class to have an almost even distribution of sectors for both the individual (40 degrees) and combined (50 degrees) movement-classes in the orientation space. However, the validity of the *linear combination* criterion can only be evaluated during the actual testing phase for real-time control.

4.2.2 Subjects

A total of twelve healthy subjects (eight males and four females, mean age $\pm$ SD = 27.67 ± 1.43 years) participated in the experiment. They all provided written informed consents prior to the commencement of the experiment. The procedures were approved by the Institutional Review Board at Nanyang Technological University.

4.2.3 Experimental Setup

The muscle activities of the subjects were recorded using a wireless EMG system (Trigno wireless, Delsys Inc.), and were acquired using a real-time data acquisition board (Quanser QPIDe), controlled in Simulink (Mathworks). The Trigno EMG sen-

sors employ a proprietary four silver bar contacts for detecting EMG signal at the skin surface (<https://www.delsys.com/>). The acquisition frequency was set at 1 kHz, and the output of the decoder during real-time control was averaged using a 10-sample moving window. The skin preparation for the electrode placement were followed according to the SENIAM protocol [142], and a total of six electrodes were evenly placed around the thickest part of the forearm (approximately one-third of the forearm distance from the elbow joint) where most of the wrist and hand muscles are concentrated. The electrodes were not specifically placed on any muscle. This was done in purpose to be able to minimize the calibration procedures as much as possible, and to improve the usability and wearability for the user. A virtual avatar consisting of the wrist and hand articulations was displayed on a screen to provide visual feedback to the user in real-time, and the different configurations for the various individual and combined motions of the avatar are as shown in Figure 4.2. The myoelectric signals are pre-processed before the analysis in order to remove noise and baseline shifts. The signals are first full-wave rectified and passed to a low-pass filter (second order Butterworth filter with a cut-off frequency of 8 Hz) to obtain a linear envelope of the signal. The signal offset is removed by subtracting the mean value of each EMG channel during the rest phase.

4.2.4 Experimental Protocol

The experiments were split into two phases:

Calibration Phase: During this phase, a GUI instructs the subjects to perform each of the individual movements, as shown in Figure 4.3. Each motion is performed four times, with three seconds of motion followed by two seconds of rest, and the data acquired during this phase is used to build the subject-specific decoding model.

Online testing phase: The performance of the decoder is tested for real-time control in this phase. The output of the decoder is translated on the screen as a movement of the avatar, as depicted in Figure 4.3. The avatar is initially in a neutral position when the subject starts the experiment. The aim of the subject is to transition the avatar from the neutral pose to the target configuration of the requested movement, which is displayed on the top-left corner of the screen. The task is considered successful,

Figure 4.2: Target configurations that the virtual avatar is designed to configure into, depending on the decoder output.

only upon reaching the target position for the requested movement and holding the pose for 0.2 seconds. A minimum jerk trajectory [128] is used to control the position of the avatar; the trajectory planning algorithm produces smooth motion profiles from one configuration to another, similar to the strategy used by humans in moving the limbs, thereby ensuring a natural motion of the avatar as much as possible. The user is required to consistently produce the target motion-class in order to reach the target configuration, while the avatar returns to the neutral configuration when the user relaxes his/her muscles.

The experiment was designed such that the users were required to simultaneously execute both the respective individual motions to be able to successfully complete a combined motion task. It should be noted that the combined task cannot be com-

pleted by strictly performing only individual motions, one after the other in series. Though, the users were allowed to initiate the combined movement by executing either of the two respective individual motions, they are still required to simultaneously and consistently execute both the respective individual movements to be able to reach towards the target and complete the task. This sequential decoding strategy is not an efficient way of performing the combined task, compared to when the user performs the task by instantaneously and simultaneously executing both the respective simple movements in a consistent manner, to successfully transition the avatar from the initial configuration to the target posture. The users were encouraged to use the latter strategy as much as possible to perform the tasks.

The online decoding experiments were split in two blocks to prevent muscle fatigue to the users, where each block consists of ten repetitions of each of the eight movements, performed in a pseudo-random order. The task is considered incomplete if the desired movement of the avatar is not performed within twenty seconds, after which a new task begins.

Figure 4.3: Decoding model testing phase a) Calibration phase: Each user is instructed to perform a movement 4 times (alternating between three seconds of movement and two seconds of rest). A timer is shown on the screen to provide feedback. b) Online testing phase: The task to be performed is presented on the screen, and the movement performed by the user is decoded in real-time to control the motion of the virtual avatar. Visual feedback of the decoding is constantly provided, and auditory cues are provided upon successful task completion.

4.2.5 Intrinsic dimensionality estimation

A primary reason for task-failure when a user wants to strictly execute an individual motion, is the inadvertent and incorrect prediction by the decoder as a combined movement instead of the intended individual motion [172]. Therefore, it is very important to accurately evaluate and predict whether the user is intending to perform an individual movement or a combined movement, to help improve the robustness and reliability of the decoder. Once it is determined, the decoding strategy can be streamlined to classify either individual or combined movements. In this study, we will be utilizing the strategy called intrinsic dimensionality estimation (IDE) to identify if the executed movement is a simple or compound motion, which has already been introduced in the work by Amsuess et. al, [172]. This process is used to identify if an unknown feature vector data belongs to a set of previously observed training data or not and is generally referred to as novelty detection [174] or one class classification [175]. In this case, the training feature vector data-set is split into four groups, one for each individual motion; a novelty detection algorithm is used to train and determine a metric corresponding to each group. This metric is used to determine if a new unknown feature vector belongs to any of the individual motion or not and if it doesn't, the data is predicted to belong to either one of the combined motions.

In this work, the novelty detection is implemented using the Mahalanobis distance (MD) measure on the LDA transformed data in order to determine whether the feature vector data at any time-sample, belongs to an individual movement or a combined movement. The MD measure has shown to be computationally efficient and perform better compared to other IDE algorithms [172]. In this case, the MD algorithm is performed on the three-dimensional LDA transformed data consisting of only the individual movements obtained during the *calibration phase*. The MD algorithm generates a distance measure for a feature vector data with respect to a group of feature vector data (data belonging to a movement class). In general, the MD measure is calculated as shown below:

$$d_{MD} = (x - \mu)^T \Sigma^{-1} (x - \mu) \quad (4.5)$$

where x represents the feature vector, μ and Σ are the mean and the covariance matrix of the data belonging to the group. The mean and standard deviation of the MD measure for each of the feature vector data in a particular movement class with respect to the entire data in the same movement class is calculated as shown below in order to identify the threshold for discrimination.

$$\begin{aligned}\mu_{MD}^i &= \sum_{j=1}^{N_s} (x_j^i - \mu^i)^T \Sigma_i^{-1} (x_j^i - \mu^i) \\ \sigma_{MD}^i &= \sum_{j=1}^{N_s} (x_j^i - \mu_{MD}^i)^2\end{aligned}\tag{4.6}$$

where μ_{MD}^i and σ_{MD}^i are the mean and standard deviation values for each movement class, x_j^i is the j^{th} feature vector data in the i^{th} movement class, and μ^i and Σ^i are the mean and covariance matrix of the feature vector data in the i^{th} movement class. During the *online testing phase*, the MD measure is evaluated on the three-dimensional LDA transformed feature vector with respect to each of the individual movement feature data cluster (recorded during the *calibration phase*) to determine if the measure lies within the threshold for the respective movement class. The threshold is set to the mean value plus two standard deviations for each movement class.

4.2.6 Performance Metrics

We use four measures (three of them are derived from Li et al. [154]) to quantify the performance of the decoding model for online classification are as follows.

1. *Motion selection time*: It is the time taken by the decoder to accurately predict the desired motion-class, i.e. the time from when the subject transitions from the rest state (movement onset) to the first instant the decoder predicts the requested movement-class. The user is requested to relax to ensure that the decoder is outputting the rest state before they start performing the task. In the case of combined movements, it is calculated as the time from the onset

of the first detection of movement to when the decoder accurately predicts the simultaneous movement.

2. *Motion completion time*: It is the time taken to complete the requested task, and is calculated from movement onset(as shown in Figure 4.4) to when the virtual avatar reaches the target configuration for the requested motion-class. Successful completion of the task is guaranteed only upon reaching the desired configuration pose and maintaining the configuration for 0.2 seconds.
3. *Online classification accuracy*: The accuracy in decoding for each successfully completed movement task is represented by this metric. In the case of combined movements, the accuracy is calculated by including the accuracy of simultaneously predicting the movement, and the accuracy of predicting the respective individual movements. This is done so as to accommodate both sequential and simultaneous decoding in the case of combined movements. The accuracy is evaluated as the ratio of the number of correctly classified samples to the total number of samples in a particular motion trial.

$$Accuracy = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{u_i}{u_i + v_i} \quad (4.7)$$

where N_t represents the number of successfully completed trials in a particular motion-class for a subject. u_i and v_i represents the number of correctly and incorrectly classified samples respectively in a particular trial i . Figure 4.4 represents the above three performance metric using an example of wrist extension motion-class.

4. *Efficiency coefficient*: This is defined as the ratio between the shortest (optimal) time required to complete the task and the actual time taken to complete the task, and expressed as a percentage. This metric is similar to the one used in [158], where instead they are calculated in terms of the optimal distance from the initial to the target. It is especially useful in the case of a combined movement task, to understand the efficiency of the user in simultaneously producing both the respective individual motions.

Figure 4.4: Metrics used for performance evaluation, explained using an example of wrist flexion and hand open motion.

Statistical analysis using a student t-test at the 5% significance level is performed in order to evaluate the difference in the performance measures between individual and combined movement classes.

4.3 Results

The data obtained during the *calibration phase* for a representative subject is shown in Figure 4.5. The LDA transformation in the three-dimensional space is shown in Figure 4.5 (A). Figure 4.5 (B) indicates the pure two-dimensional LDA projection (projection of the three-dimensional data obtained after LDA transform on the x-y plane without performing optimal rotation), whereas Figure 4.5 (C) indicates the representation involving both LDA projection and optimal rotation. Both these projections (plot B and C) facilitates in the discrimination of the individual motions, but only the

latter projection (plot C) can ensure the validity of the *orientation constraint* criteria. Therefore, the LDA plus optimal rotation transform helps in ensuring the validity of the *orientation constraint* criterion in the best possible way.

Figure 4.5: A) The plot represents the three-dimensional LDA transformed EMG data of the 4 individual movements. B) The two-dimensional projection is represented in this plot, and it fails to meet the *orientation constraint* criteria, thereby invalidating the proposed decoding model. C) The transformed data after the optimal rotation and followed by two-dimensional projection is represented in this plot. It can be noticed that validity of the *orientation constraint* criteria is ensured, and the dotted lines indicate the boundaries for discriminating the various movements.

Figure 4.6 shows the EMG data projected on a two-dimensional space of a representative subject, during the *online testing phase*. The plot on the left indicates the data from the twenty trials for each of the individual movement-classes, whereas the plot on the right are those belonging to the combined movement-classes. It can be noticed that the data from the combined classes do indeed lie in the orientation space between the respective individual class data, thereby validating the *linear combination* criterion. Therefore, the LDA projection followed by the optimal rotation ensures the validity of both the *orientation constraint* and *linear combination* criteria,

thereby enabling the working of our proposed decoding strategy.

Figure 4.6: The two-dimensional projection of the EMG data of a representative subject during the *online testing phase* is indicated. The plot on the left represents the data for the twenty trials for each of the individual movements, while the plot on the right correspond to the data of the combined movement trials.

The comparison of the accuracy with and without IDE is shown for each subject in Figure 4.7, where the individual motion data obtained during the *online testing phase* is used to evaluate the efficacy. The rate of misclassification of an individual movement as combined movement is shown to decrease for most of the subjects, and in such cases the prediction accuracy for individual motions have respectively improved. A one-way repeated anova test was performed to evaluate the significance in the differences between the misclassification rate. We observed a high significant difference ($p = 0.002$) with an F-ratio of 15.815.

Motion Selection Time: The average time taken to correctly select the desired motion class, across all subjects and motion classes is 0.52 ± 1.07 seconds. The mean selection time is higher in the case of simultaneous motions (0.78 ± 1.20) when compared to individual motions (0.28 ± 0.87). A significant difference between individual and combined data-sets was found.

Motion Completion Time: The average time taken to complete each task across all the subjects and motion class is 2.53 ± 2.41 seconds. A statistical significance is observed in the average values between individual (2.04 ± 2.02) and combined motions (3.06 ± 2.66), with the average time higher in the case of combined movements.

Figure 4.7: Bar plots indicating the accuracy of decoding of the individual movements, and the misclassification rate for all the subjects. A comparison of the accuracies with and without the IDE technique is shown to highlight its importance.

Online Classification Accuracy: The average classification performance of the decoder for all the subjects and across all the motion classes is $87.86 \pm 19.79\%$. There is also a statistical difference in the classification accuracy between individual ($82.1 \pm 23.56\%$) and combined motions ($93.94 \pm 12.15\%$), with combined movements having higher classification accuracy.

Efficiency Coefficient: The average efficiency coefficient of the decoder for all the subjects and across all the motion classes is $65.54 \pm 32.31\%$. There is also a statistical difference in the efficiency values between individual ($74.0 \pm 31.2\%$) and combined motions (56.64 ± 31.06), with combined movements having lower values in general.

Figure 4.8 represents the polar plot indicating the mean and standard error in the case of each of the movement classes across all subjects, for each of the performance measures.

The confusion matrix shown in Figure 4.9 reports the inaccuracy of the decoding model in predicting the user intention. We can notice that the accuracy of decoding the combined movements simultaneously, is low compared to that of the individual movements. This only means that an intended combined motion was performed

Figure 4.8: Polar plot for the various performance metrics. Black lines and the dotted lines indicate the mean and standard error respectively in each motion-class across all subjects.

sequentially, meaning that user starts with one individual motion-class followed by simultaneously performing the other respective class at some point in time to successfully complete the task. According to previous studies, unintended simultaneous motions were more detrimental to the control than unintended sequential motions [172]. The reason for a sequential approach could either be because of the higher threshold set in the MD algorithm to differentiate between individual and combined movements, or because the user intentionally preferred a sequential approach to complete the combined motion task. However, we observed a gradual change, from a sequential decoding to a more simultaneous decoding strategy, by the subjects as the trials progressed.

Figure 4.9: Plot shows the confusion matrix of the classification accuracy concerning all the motion tasks.

In order to verify the learning trend, we measured the gradient of the line fitting the classification accuracy values during the twenty repetitions vs the gradient of the motion selection time values, in the case of combined movements for each of the twelve subjects. The motion selection time would result in a higher value in case the user sequentially (and not synchronously) performed the individual movements corresponding to a combined motion. Hence, having a smaller motion selection time would directly imply an improvement in classification accuracy of simultaneous decoding. A decreasing movement selection time over the course of the online experiments would then correspond to an increasing trend in the accuracy of simultaneously decoding the combined motions. This might suggest that the subjects progressively learn to simultaneously coordinate the movements to efficiently reach the target during the online testing. Figure 4.10 shows the plot of the gradient of accu-

racy trend (slope of the line fitted to the accuracy values for a movement-class during the 20 repetitions) versus the gradient of the motion selection time for the combined movements. Positive slope values on the x axis can be observed in majority of subjects, which indicates the presence of a learning effect. We did not perform a familiarization phase because our work does not contemplate any task which includes remapping of motor commands, kinematics or haptics, but rather the subjects were requested to replicate a motion task presented on a screen by a virtual avatar. A negative correlation -0.55 is observed between the two measures, and the correlation is found to be significant ($p < 0.05$).

Figure 4.10: Correlation plot indicating the gradient of the classification accuracy trend vs the gradient of the motion selection time trend for all the subjects in the case of combined movements. The red line is a linear fit to the data, and the negative slope indicates a learning trend implying a faster transition from sequential to simultaneous activation of the respective individual movements that entails the combined movement.

4.4 Discussion and Conclusion

The online testing of the proposed decoding strategy indicates good classification accuracy for both individual and combined motions involving the hand and wrist DOFs. Low-dimensional representation using the LDA plus optimal rotation transformation algorithm provides the basis for discriminating between individual and combined movements in a two-dimensional representation. We believe, that our approach is novel, and incorporates the strength of the LDA technique to build an algorithm capable of decoding both individual and simultaneous movements. As previously mentioned, the method proposed by Jiang et al for simultaneous motion decoding uses an NMF algorithm (unsupervised) to perform dimensionality reduction; one drawback of their approach is the need to determine a correction factor after the calibration in order to account for any potential reversal of direction due to the indeterminacy of the NMF algorithm [158]. Our proposed decoding model does not have any directional indeterminacy due to fact that LDA is a supervised algorithm where both the agonist and antagonistic movements in a DOF are labeled. However, it is one of the first algorithms to develop a strategy for decoding both individual and combined motions, by recording data from the singular movement, which is aligned with our proposed decoding strategy. While a comparison between the two approaches in terms of accuracy of decoding is not possible at the moment, due to the fact our proposed decoding strategy is built to perform discrete classification of movements rather than a proportional regression-based approach by the other group. However, we have added a table (Table 4.1) to make a generic comparison of the efficiency coefficient metric in both the cases.

We notice better efficiency values while using our LDA based approach ($mean = 63.83\%$) compared to NMF based approach ($mean = 56.96\%$) by Jiang et al. [158], where both strategies use a position control model for the movement of the avatar or cursor. Though, the nature of the tasks is different in both the cases, this comparison is only meant to provide a coarse evaluation of our approach when compared to others. However, our next step will be in extending the usage of the decoding strategy to include proportional control, and hence an evaluation of the performance differ-

Table 4.1: Efficiency Coefficient Comparison.

NMF approach by Jiang et al. [158]		Our proposed LDA approach			
Sub	Efficiency Co-efficient	Sub	Efficiency Co-efficient	Sub	Efficiency Co-efficient
H2	66.87 ± 24.36	S1	74.14 ± 10.28	S7	52.57 ± 19.53
H5	64.01 ± 22.74	S2	60.73 ± 22.90	S8	60.37 ± 24.03
H7	48.76 ± 23.30	S3	59.72 ± 26.23	S9	61.71 ± 24.48
AG3	48.21 ± 18.95	S4	63.16 ± 24.56	S10	56.83 ± 25.57
-	-	S5	57.88 ± 21.97	S11	81.18 ± 19.77
-	-	S6	68.70 ± 25.37	S12	68.93 ± 27.25

ences would be more appropriate. On the other hand, the approach by Young et al. is based on a strategy that involves recording data from both simple and multiple motions. However, the main aim of this study is primarily to introduce and evaluate the efficacy of a novel low-dimensional and computationally efficient decoding strategy capable of simultaneous decoding, by recording only the individual motions.

Another aspect of our proposed decoding strategy is the potential to incorporate a modular approach, whereby scalability in terms of the number of DOFs can be achieved without increasing the complexity. This means that any n -DOF task ($n > 2$) could be split into smaller two-DOF task submodules, and the outputs can then be combined to perform simultaneous decoding. With a 'divide and conquer' strategy, along with the IDE technique to distinguish between individual and combined movements, our algorithm could potentially aid in increasing the number of DOFs, and this critical challenge will be an important focus for future works. Together with low-dimensionality of control and reduced computational cost, our aim is to implement the control algorithm in an embedded computing platform, to enable portability of the processing unit and perform faster real-time control in applications such as myoelectric-based prosthesis or exoskeletons.

One limitation of our proposed decoding strategy to be considered for future experiments is the lack of proportional control in movement position. However, the algorithm could be extended to incorporate proportional myoelectric control by evaluating the magnitude of the feature vector in the 2-dimensional plane after the modified-LDA transformation. The amplitude of the feature vector provides an estimation of

the effort exerted by the user, and normalization procedures can be performed to ensure similar peak velocities across all classes. An optimization algorithm could be built to further reduce the calibration time especially for calculating the optimum rotation matrix. A cost function could be used to implement a gradient descent-based approach to arrive at the optimum Euler-angle values, instead on calculating the cost for all possible combinations of Euler-angles.

Chapter 5

Position and Stiffness Modulation of a Wrist Haptic device using Myoelectric Interface

5.1 Introduction

5.1.1 Background

The capabilities of myoelectric-based control in human-machine interface applications have been advancing in the recent years; starting from proportional position control, to simultaneous control of multiple degrees of freedom, and now more recently incorporating the capability for users to modulate impedance of the robotic device in real-time. Humans have the inherent capability to actively modulate the impedance characteristics in the joints, thereby allowing for an efficient way of performing tasks and a safer way of interacting with unknown environment [45, 46, 47, 48, 49, 50]. Impedance modulation allows for lowering the impedance levels so as to perform exploratory/collaborative tasks, or increasing the impedance levels to overcome external disturbances while maintaining the posture [47]. The regulation of impedance has been stressed in literature by Abul-Haj et al [176], and recent experiments have emphasized the importance of the task-dependent impedance modulation for an improved and efficient user performance in performing tele-manipulation

operations in a prosthesis device [27]. The ultimate goal is to be able to incorporate these motor control strategies used by humans in performing tasks, to anthropomorphic robotic devices such as prosthesis and exoskeletons. The term impedance is a collective term for three elements namely stiffness, damping and inertia, out of which the stiffness element is considered to be of prime importance and is the main focus of this paper. Stiffness around a degree of freedom can be directly modulated by co-contracting the corresponding agonist-antagonistic muscle pairs. Damping cannot be independently modulated by the humans [177] and depends on the position of the joint and the co-contraction level of the muscles [178]. Whereas, the inertia of limbs can be modulated by changing the limb configuration with respect to the torso [179].

Recent advances in technology have enabled variable impedance characteristics to prosthetic and orthotic devices, but there are some limitations associated with its regulation. Impedance regulation is difficult especially when operating beyond the permissible bandwidth of the actuators involved, and the conventional electromechanical robots have high impedance above their controllable bandwidth [180, 181]. Impedance modulation can be implemented either by means of a software algorithm, or directly incorporating it in the mechanical design either using series elastic actuators [181] or variable stiffness actuators [182, 55]. Sensinger and Weir have shown that adding compliance in the system ensures a lower impedance level in the system while operating beyond its bandwidth [181, 54]. However, Rao and Hocaoglu et al. [182, 55] have used variable stiffness actuation in their robotic device in order to modulate the stiffness, and such a system also allows for regulation of impedance over the whole frequency spectrum, and is also energy efficient compared to other approaches.

Myoelectric signals could be employed in evaluating both the joint position and stiffness values of the user to control either a prosthetic device or a robotic manipulator [54, 182, 55, 183]. It is mentioned in literature that the velocity at the joint is proportional to the amplitude of the filtered electromyographic (EMG) signals [184]. The difference between the normalized surface EMG signals of the agonist and antagonist muscles is generally used to determine the speed and direction of the concerned

degree of freedom; a threshold is set in order to distinguish between rest and motion intention. This motion control paradigm is referred to as proportional velocity control (PVC) [54], where the position estimates are used to determine the desired trajectory of the robot, and an impedance controller is used to ensure the tracking. Estimating stiffness values during a dynamic task is a challenging task. It is well established fact there exists a non-linear relationship between muscle tension, length and velocity, for given level of muscle activity [55]. Moreover, the length of the moment arms required to calculate the torque produced by the muscle also changes with the joint position [185]. Non-linear models based on Hill's muscle model are generally employed to calculate the muscle tensions and moment arms at the joints. However, extensive calibration procedures are necessary to accurately identify the parameters of the model, as in the case by Nikos et al [53]. A simplified linear time-invariant model called index of muscle co-contraction around the joint (IMCJ) have also been proposed to estimate the dynamic joint stiffness values. Though, the stiffness estimates based on the IMCJ method are inevitably erroneous, it has been shown in previous experiments that the subjects can quickly learn to adapt to this coarse level of stiffness adjustments in performing tasks [186, 54].

5.1.2 Aim

The concept of user modulated stiffness control using the IMCJ model have generally been employed in tele-manipulation tasks using either a prosthetic limb [54, 55] or a robotic manipulator [27]. However, in this study we are interested in implementing the IMCJ model in the context of an orthotic device and enable the modulation of both position and stiffness, when the user is haptically coupled with the robot. The objective of this study is to evaluate the performance of an impedance control architecture based on the simplified IMCJ model and identify if the implementation could translate well also in the case of an orthotic device, as with previous studies using prosthetic devices [187]. It is very important to understand if the subjects are capable of modulating both position and stiffness in performing a trajectory tracking task with external force disturbances, while ensuring smoothness and accuracy. The results presented in this chapter can be found in [188].

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5.2 Methods

5.2.1 Experimental Setup

The experiment was designed to test the working of the control paradigm in a one degree of freedom task involving the wrist flexion/extension. A wrist robot consisting of three degrees of freedom (wrist flexion/extension, abduction/adduction, and pronation/supination) was utilized for this purpose, and allows for full range of motion for the human wrist [6], and the setup is shown in figure 5.1. The handle of the robot has been modified in order to ensure that the users didn't need to grasp the handle in order to interact with the robot. This is also to ensure that only wrist flexion/extension movements were performed, and prevent voluntary muscle activity due to grasping the handle by the hand. The other two degrees of freedom were blocked to prevent unwanted movements, and also to avoid the effort required in compensating for gravity forces while holding the initial configuration. An axial force sensor (Optoforce OMD-30-FE-450N) is attached at the interface of the handle in order to measure the interaction force between the robot and the user. It can measure up to 450N of force in compression and 150N in tension, and has a sensitivity of 0.027N. Two surface EMG electrodes (Delsys Trigno Wireless) were used to acquire myoelectric signals from flexor carpi ulnaris (FCU) and extensor carpi radialis (ECR), which are respectively responsible for wrist flexion and wrist extension. The Trigno EMG sensors employ a proprietary four silver bar contacts for detecting EMG signal at the skin surface (<https://www.delsys.com/>) and the sampling rate was set at 1 kHz. The skin preparation and electrode placement on the various muscles were followed according to the protocol mentioned in the SENIAM repository [142]. A custom program for the myoelectric-based control is built in Simulink, where the EMG signals

are acquired and processed in real-time and the control outputs are translated into the motion of the robot.

Figure 5.1: The Wristbot robot with 3 degrees of freedom, namely wrist flexion/extension, wrist ulnar/radial deviation and wrist pronation/supination [6].

5.2.2 Subjects

A total of 6 healthy subjects (6 males, age 26.66 ± 3.38 years) participated in the experiment, and they all provided written informed consents. The procedures were approved by the Institutional Review Board at Nanyang Technological University.

5.2.3 Control Paradigm

The control paradigm follows an impedance control algorithm [189], and is used to drive the robot arm. The dynamic equation of the control algorithm is given by

$$\tau = K \times (\theta_d - \theta_a) - b \times \dot{\theta}_a + \tau_{ext} \quad (5.1)$$

where τ is the input torque to the robot, θ_d is the desired trajectory profile for the robot motion, θ_a is the actual position of the robot, $\dot{\theta}_a$ is the actual velocity of the robot, K is the stiffness value of the robot joint, b is the damping factor and is fixed

such that the system's stability is ensured even at the highest level of stiffness values, and τ_{ext} is the external torque acting on the system.

The raw EMG signals from FCU and ECR are first pre-processed (rectification followed by low-pass filtering), and then normalized by their respective maximum voluntary contraction (MVC), and are represented as F and E . MVC is calculated by instructing the users to perform isometric contractions and pushing as hard as possible against a stationary object, for about 3 to 4 times. The average of the peak EMG signal values is used to normalize the EMG signals, to have a range between 0 and 1. Two thresholds C_1 and C_2 , one for each muscle are set in order to differentiate between rest and movement. The relationships for position control is similar to the equations found in [54], and is shown below:

$$\dot{\theta}_d = \begin{cases} \alpha(E - C_1) + \beta & E > C_1, F < C_2 \\ \alpha(-F + C_2) + \beta & E < C_1, F > C_2 \\ \alpha((E - C_1) + (-F + C_2)) + 2\beta & E > C_1, F > C_2 \\ 0 & E < C_1, F < C_2 \end{cases} \quad (5.2)$$

where $\dot{\theta}_d$ is the desired velocity profile for the robot motion, α and β are constants which are fixed depending on the lower and upper limit of velocity set for the experiment. The velocity ranges between 0.1 rad/s and 1 rad/s . The velocity is then integrated in order to obtain the desired position x_d at each time step.

The stiffness equation is based on the IMCJ model [55], where stiffness is given by

$$K = \begin{cases} \lambda(E - C_1) + \gamma & E > C_1, F < C_2 \\ \lambda(F - C_2) + \gamma & E < C_1, F > C_2 \\ \lambda((E - C_1) + (F - C_2)) + 2\gamma & E > C_1, F > C_2 \\ \gamma & E < C_1, F < C_2 \end{cases} \quad (5.3)$$

where λ and γ are constants which are tuned based on the minimum and maximum level of stiffness desired for the experiment: the stiffness range is between 10 Nm/rad and 20 Nm/rad .

To have an effective control, it is important to have simultaneous and independent control of both position and stiffness. Based on the above equations, it is possible

to modulate the stiffness with and without utilizing co-contraction strategies. The velocity and stiffness profiles are linearly dependent on the EMG activity in the case where only one muscle is active (non co-contraction case). Hence, it is difficult to produce high stiffness values to the robot at low velocities, and vice-versa. However, it is possible to have higher stiffness values at lower velocity while co-contracting both the muscles, but it is done at higher energy expenditure. The schematics of the control paradigms for position and stiffness modulation, along with the impedance control architecture is represented in figure 5.2.

Figure 5.2: Schematics of the impedance control architecture along with user modulated position and stiffness values using EMG signals.

5.2.4 Experimental Task

The task was designed to encourage the need for users to be able to co-contraction the muscles and modulate stiffness, while being able to control the position of the robot. As such, a one dimensional trajectory tracking task similar to the task in Blank et al. [27], was designed. The desired trajectory to track is based on the equation given below:

$$\theta_t = 20\sin(t + \frac{\pi}{6}) + 20\sin(2t + \frac{2\pi}{3}) \quad (5.4)$$

where the parameters were chosen such that the desired trajectory covered the workspace range of $\pm 40 \text{ deg}$ and moves at a reasonable pace for the subjects to track, and these

parameters are constant throughout the experiments for all the subjects. The users are also able to anticipate how the motion trajectory will advance, since the newer portions of the trajectory moves from the top to the bottom of the screen, as can be seen in the figure 5.3 (B). While performing the tracking task, external forces are generated which try to push the user away from their current position. The direction and magnitude of the force are graphically displayed using an arrow as shown in the figure 5.3 so that the subjects can also perceive a visual feedback of the forces in addition to the haptic feedback. The time varying force field is generated by the equation given below, and the parameters were chosen such that the forces were out of phase with the desired trajectory, and had a different time-period so as to make it difficult for the subjects to anticipate the direction and magnitude of the disturbance.

Figure 5.3: The experimental setup showing the subject coupled to the wrist robot with an illustration of the trajectory tracking task is shown on the expanded window. The actual end-effector position of the robot is mapped to the yellow colored cursor, whereas the red colored cursor indicates the desired position to be tracked by the user at any instant, and the evolution of the tracking trajectory is indicated by the small red balls which move from top to bottom. The red arrow indicates the direction and magnitude of the external disturbance acting on the system.

$$\tau_{ext} = 3\sin(t + \frac{\pi}{4}) + 3\sin(2t + \frac{7\pi}{12}) \quad (5.5)$$

5.2.5 Experimental Protocol

The trajectory tracking task was split into two parts: *experiment 1* where the subjects are advised to not co-contract their muscles while performing the tracking task, whereas in *experiment 2*, the subjects are requested to co-contract their muscles in order to perform the same task. Ten trials of each experiment was performed by the user, and each trial of trajectory tracking task lasted for 90 seconds. In order to ensure that the subjects do not co-contract during *experiment 1*, and co-contract during *experiment 2*, the cursor that corresponds to the end-effector of the robot is color coded to provide visual feedback. The cursor turns green when the user is only performing wrist extension, blue during wrist flexion, red during co-contraction, and yellow during rest. Also, the size of the cursor varies proportional to the muscle activity, which provides feedback regarding the effort applied by the user in performing the task.

5.2.6 Performance Metrics

1. **Tracking accuracy:** This metric is used to quantify the accuracy with which the user tracks the desired trajectory. The root means squared error between the actual and the desired trajectory is used to define the tracking performance. This measure is calculated over the entire trial duration of 90 seconds. The lower the value, the better the performance. The relation is given by:

$$\text{Tracking accuracy} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\theta_t^i - \theta_a^i)^2} \quad (5.6)$$

where θ_t and θ_a are respectively the target trajectory and actual trajectory of the robot at each time step i , and i varies from 1 to the number of samples N in 90 seconds.

2. **Movement smoothness:** Smoothness measure is important to understand the quality of the user's movement, and are considered to be the optimal and efficient of performing a task. An intermittent and irregular movement is an indication of lack of motor coordination. There are a number of metrics used

to quantify smoothness of movement, and one such measure which is dimensionless and independent of movement duration and amplitude is the spectral arc length (SPARC) [190]. It is defined as:

$$SPARC = - \int_0^{\omega_c} \left[\left(\frac{1}{\omega_c} \right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega} \right)^2 \right]^{\frac{1}{2}} d\omega ; \quad (5.7)$$

$$\hat{V}(\omega) = \frac{V(\omega)}{V(0)}$$

$$\omega_c = \min \{ \omega_c^{max}, \min \{ \omega, \hat{V}(r) < \bar{V} \ \forall \ r > \omega \} \}$$

where ω_c is the cut-off frequency, ω_c^{max} is the upper-bound for the cut-off frequency, $\bar{V}$ is the threshold on the normalized magnitude spectrum $\hat{V}(\omega)$. The recommended value as suggested by the authors are $\bar{V} = 0.05$, and $\omega_c^{max} = 20\pi$. The higher the values, the better the smoothness measure.

3. **Interaction force:** The forces acting at the interface between the robot and the human is measured in order to understand the level of discomfort experienced by the user. The mean normal force acting during each trial is evaluated and is as shown below:

$$Interaction \ force = \frac{1}{N} \sum_{i=1}^N Fz_i \quad (5.8)$$

where Fz_i is the normal force measured at the i^{th} time step and i varies from 1 to number of samples N in 90 seconds.

4. **Muscular effort:** EMG signals provide a measure of the effort applied by the user. Two EMG channels corresponding to the flexor and extensor muscles are summed up together and their mean activity for each trial is evaluated as follow:

$$Muscular \ effort = \frac{1}{N} \sum_{i=1}^N (F_{filt}^i + E_{filt}^i) \quad (5.9)$$

where F_{filt}^i and E_{filt}^i are the filtered non-normalized EMG activity of the flexor

and extensor muscles respectively at the i^{th} time step. and N is the total number of time steps.

Statistical analysis is performed using a student t-test method, in order to understand the significance between the two experiments, and the data were tested at the 5% significance level.

Figure 5.4: A typical trial of a representative subject: A) The entire trajectory during the 90 second trial is indicated in black dotted line; the solid grey and black lines indicate the trajectory tracked by the subject during *experiment 1* and *experiment 2* respectively. B) The magnitude and direction of external force acting on the wrist robot is indicated in the black line. C) The grey and black lines indicate the interaction force acting between the robot and the subject during *experiment 1* and *experiment 2* respectively. D) The grey and black lines indicate the EMG activity of the subject during *experiment 1* and *experiment 2* respectively. Solid lines indicate the activity of the flexor carpi ulnaris (FCU), while the dotted lines indicate the activity of the extensor carpi radialis (ECR).

Figure 5.5: The mean and standard deviation for the performance indicators across all the subjects and trials in both *experiment 1* and *experiment 2* are indicated.

5.3 Results

A typical trial of one subject performing the tracking task is shown in figure 5.4 indicating the trajectory tracked by the subject, external forces acting on the robot, interaction forces acting between the subject and the robot, and the EMG activity in both the experiments. The mean and standard deviation of the all the performance indices across all subjects and trials for both the experiments are shown in figure 5.5. The average RMSE value across the subjects and trials in the case of *experiment 1* is $9.01 \pm 3.5 \text{ deg}$, whereas in the case of *experiment 2* is $5.39 \pm 1.53 \text{ deg}$. There is a high statistical difference in the tracking accuracy between *experiment 1* and *experiment 2* ($p < 0.05$). This clearly indicates better performance using co-contraction technique in order to overcome time varying forces while tracking a desired trajectory.

The smoothness indicator also indicates a better performance in the case of *experiment 2* when compared to *experiment 1*. The mean spectral arc length values across the subjects and trials in the case of *experiment 1* is -50.99 ± 10.92 and *experiment 2* is -37.7 ± 6.46 . A statistical difference between the two experiments is also observed in the case of movement smoothness ($p < 0.05$).

The average interaction forces in the case of *experiment 1* is $0.81 \pm 0.15 \text{ N}$ and in *experiment 2* is $0.77 \pm 0.2 \text{ N}$ interaction forces are generally lower in the case of *experiment 2* when compared to *experiment 1*. However, the difference is not statistically significant.

The mean muscular activity across the ten trials and across subjects in *experiment 1* is $0.017 \pm 0.003 \text{ V}$ and in *experiment 2* is $0.032 \pm 0.0084 \text{ V}$, . These indicate a higher

effort involved in the case of *experiment 2* than in the case of *experiment 1*, and the difference is statistically significant ($p < 0.05$).

5.4 Discussion and Conclusion

The results indicate better overall performances while using co-contraction techniques, in scenarios where unpredictable external forces are involved in perturbing the task. Indeed, the performances are comparable with previous studies, where the experiments were performed in the context of a prosthesis control or for tele-manipulation [187, 27]. Stiffness modulation plays a very important role in successfully performing activities of daily living, and as such it is very essential in transferring these skill-sets to mechatronic entities involving human machine interactions, in order to have better transparency in the way humans interact with robots. It is important to mention that humans utilize co-contraction strategies voluntarily depending on the nature of the task, but not consciously knowing that they are activating both the agonist-antagonist pair at the same time. Whereas, in the case of *experiment 2* the subjects were specifically instructed to co-contrast both the flexor and extensor muscle in order to perform the task. And, the performance of the subjects for both tracking accuracy and movement smoothness in the case of *experiment 2* has been consistently better compared to *experiment 1*, which indicates that the control strategy was intuitive and natural for the subjects in performing the task.

In general, stiffness modulation is performed in both the experiments irrespective of whether subjects co-contrast or not. However, the independence between stiffness and position modulation is achievable only in the case of co-contraction, whereby it is possible to obtain high stiffness values even at lower speeds. This is probably a main reason for a smoother and stable tracking in the case of *experiment 2*. The variances in the muscular effort plot indicates that subjects preferred to vary their activation patterns more while co-contracting, in the case of *experiment 2*. Moreover, we can notice an interesting trend in the correlation coefficients of the RMSE vs EMG values across trials, and the SPARC vs EMG values across trials for each subject as shown in figure 5.6. There is a consistent positive correlation in both the plots in

Figure 5.6: The correlation index of the RMSE vs EMG activity, and the SPARC vs EMG activity across the ten trials for each subject are indicated in the plot.

the case of *experiment 2* compared to that of *experiment 1*. This means that an increase in the EMG activity makes the user less accurate in performing tracking task whereas, it could improve the smoothness of performance. Therefore, this could indicate a trade-off between accuracy and smoothness, suggesting the need for an optimal modulation of the muscle activities to achieve better task performance. Learning effective stiffness modulation is very important in successfully performing certain activities of daily living. We believe, this control strategy could be very beneficial in the context of an exoskeleton where the user-modulated stiffness level would enable adaptive assistance to the user.

Chapter 6

Conclusion and Outlook

6.1 Summary

There is immense potential in using myoelectric signals for building intuitive human-machine interfaces especially in assistive devices such as exoskeletons and prostheses, to help people with motor impairments regain some level of independence. However, there are still quite a lot of challenges in achieving reliable decoding skills, and efficient task performance. Furthermore, it is highly critical in optimizing algorithms for efficient use in an embedded architecture, which in turn could aid in bringing these devices for usage in a daily life environment. In this thesis we have focused on highlighting the importance of synergistic features using NMF and LDA techniques which are capable of simplifying the control complexity and reducing the computational cost. We have identified and introduced learning algorithms which can make a huge impact in applications involving real-time computations, along with its ability to generalize to unseen data. We have addressed the challenge related to simultaneous decoding by proposing a novel algorithm which uses minimal calibration procedures to ensure an efficient way of classifying both simple and combined movements. Lastly, we focus our study towards the implementation of control strategy which enables subjects with the capability to modulate both position and stiffness characteristics of an exoskeleton device. Transferring stiffness characteristics from humans to robots is a great step towards ensuring transparency and safety in appli-

cations involving human-machine interactions.

6.2 Major contributions

6.2.1 Role of Muscle Synergies

The study presented in Chapter 3 focuses on comparing the two approaches in feature extraction techniques for real-time motion control of upper limb movements. Outcomes showed that the classification performance is better and more robust while using *synergy feature* than *EMG feature* sets. Apart from contrasting the performance of these two types of feature extraction strategies, the contributions of this investigation is to highlight the advantage of using the information provided by muscle synergies, to get a more accurate decoding of movements which involve a coordinated muscle activity. This approach would be highly beneficial for all those applications which rely on bio-signals in general (and not only EMG) to drive systems ranging from human augmentation to assistive technology, and this is particularly true when multiple degrees of freedom are involved.

6.2.2 Performance of ELM for real-time control

The use of ELM in developing the decoder has provided tremendous advantages with the high rate of learning, faster computational speeds and better generalization to unseen data. It is also the first time that the performance of ELM has been quantified for real-time decoding in a myoelectric-based motion decoding. This study will hopefully direct the attention of researchers in myoelectric-based motion decoding towards using ELM algorithms as viable options for real-time applications. It is worth mentioning that a robust algorithm for motion classification, would add an enormous benefit especially in those fields when a reduced muscular activity consequential to a neurological damage makes it difficult to detect the motor intention from the patient, and almost impossible to drive any kind of robotic device to support and provide assistance.

6.2.3 Simultaneous Motion Decoding

We proposed a new classification algorithm in Chapter 4 capable of decoding both individual and combined movements, but by recording EMG data from only the individual motions. The decoding strategy utilizes the computational simplicity of LDA along with the optimization principles, to build a novel classification scheme capable of simultaneous decoding. The performance of the decoder was tested in the case of a two DOF motion task involving hand and wrist movements. The results indicate good decoding accuracy for both individual and combined motions. Incorporating an IDE technique based on MD measure has helped improve the decoding accuracy and prevent inadvertent activation of combined motions when individual motion is intended.

6.2.4 User-modulated position and stiffness control

In Chapter 5 we have implemented a control strategy for online user-modulated stiffness and position control in an orthotic device, and tested its performance in a tracking task under varying external force. Our objective is to use a simplified linear-time invariant model instead of using an almost accurate model which is computationally expensive and time consuming for evaluating stiffness values, in real-time using the subject's EMG signals. Nevertheless, we were able to observe performance trends similar to those in literature which used tele-manipulation strategies in the case of a prosthetic device or a robotic manipulator, without compromising on the tracking capability of the user in a varying force field. This reaffirms the ability of the brain to adapt to a model which doesn't necessarily need to be perfect; the implications of this study is in simplification of the control strategy by building a coarse model, which can be compensated by letting the brain fine tune itself and adapt to an imperfect model.

6.3 Future Works

Our study has mostly focused on testing with a virtual avatar, which could be more practical for applications involving tele-manipulation, but does not provide a realistic scenario for an exoskeleton application. The exosuit in development at the lab currently only provides assistance for elbow flexion/extension motion with planned progress towards including shoulder joint actuation [191, 192]. In future we would like to incorporate our decoding strategy in the soft wearable exosuit with capability to incorporate simultaneous decoding of shoulder and elbow motions.

As we mentioned in Chapter 4, the proposed decoding strategy could be extended to incorporate proportional control of motions by taking into account the magnitude of the projected feature vector in the two-dimensional plane, after the LDA and optimal rotation transform. This would be followed by a comparison study with the method proposed by Jiang et al [41] to evaluate the differences in performances, since the approach followed by both the methods are similar, i.e. EMG data of only the individual motions are recorded to build the decoder. Another prospective direction would be towards adding another DOF to also include wrist pronation/supination motions; together with the other two DOFs from our study, they can improve functional capabilities for transradial amputees [193].

The concept of modulation of position and stiffness characteristics by the user using a simplified model has been implemented in a preliminary experiment on a wrist haptic device mainly to evaluate how close this strategy can translate to in comparison to an accurate model. However, the control strategy is intended to be applied in the soft exosuit which is currently under development. Further investigation along this line will be conducted in future, towards achieving a safer and transparent human-machine interaction.

Lastly, we would like to highlight the general evolutionary trend that can be observed in myoelectric based motion decoding, and would like to emphasize future research towards that direction; starting from simple *discrete classification* to *proportional position control* to *proportional and simultaneous position control* to *proportional, simultaneous position and impedance control*.

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