Task-space separation principle : from human postural synergies to bio-inspired motion planning for redundant manipulators

Tommasino, Paolo

2017

Tommasino, P. (2017). Task-space separation principle : from human postural synergies to bio-inspired motion planning for redundant manipulators. Doctoral thesis, Nanyang Technological University, Singapore.

<http://hdl.handle.net/10356/70600>

<https://doi.org/10.32657/10356/70600>

Task-space Separation Principle: from Human Postural Synergies to Bio-inspired Motion Planning for Redundant Manipulators

Paolo TOMMASINO

SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING

Supervisor:

Associate Professor Domenico CAMPOLO

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

Dedicated to my parents

Aknlowledgments

The past years have been some of the toughest, craziest and most beautiful years of my life and therefore I wish to thank all the wonderful people that made this long journey possible. First of all, I must thank Domenico Campolo that, like a 'renaissance master', has wisely and superbly 'sculpted' my mind with interesting and fascinating engineering problems and conversations. I also want to thank professors Lorenzo Masia, Etienne Burdet, Frank C. Park, Domenico Formica and the anonymous reviewers for their feedback and insights that helped improving the quality of this work. Thanks to the Robotics Research Centre staff Lim Eng Cheng, Tan Siok Kuan Agnes, You Kim San for their professionalism and cordiality. I am also very grateful to past and current members of the Synegy Lab and ARIES Lab for the wonderful time spent together inside and outside the lab. Thanks also to my long-term flatmates Paola Lova and Carlo Tiseo that have been like a 'second Italian mom' in Singapore. Last but not the least, a warm and special acknowledgement goes to my family and Karine Loh for their infinite patience, encouragement and love.

Contents

Abstract	6
1 Introduction	9
1.1 Motivation & Objective	9
1.2 Thesis outline and contribution	11
2 Background: Posture, Movement & Redundancy	13
2.1 Introduction	13
2.2 Motor redundancy and the degrees-of-freedom problem	14
2.3 Kinematic constraints and synergies in humans	14
2.3.1 Empirical motor laws	14
2.3.2 Postural constraints: Donders'law	16
2.4 Computational approaches to human motor control	18
2.4.1 Optimality-based approach and Separation Principle (joint-space)	18
2.4.2 The cybernetic approach: motion planning with internal models	22
2.4.3 Motion planning with equilibrium points and force fields	23
3 Task-space Separation Principle: a force field approach to posture and movement planning for redundant manipulators	29
3.1 Introduction	29
3.2 Lagrange Multipliers as Task-space Force Fields	30
3.2.1 Postural Control: Donders' law from static task-space force fields and intrinsic potentials	32
3.2.2 Task-space Motion Planning: a generalization	34
3.3 Application to Wrist Pointing Tasks	36
3.3.1 Wrist kinematics during pointing tasks	38
3.3.2 Donders'law for the wrist	40
3.3.3 Simulated wrist pointing tasks	41
3.3.4 Pointing with the velocity resolution control: null-space hysteresis	43
3.3.5 PMP vs λ_0 -PMP: repeatability and posture/movement problem	46
3.3.6 Task-space optimal control and holonomic constraints	51
3.4 Conclusion	55

I	Posture	63
4	Capturing Human-like Postural Kinematic Synergies via Non-linear Inverse Optimization	65
4.1	Introduction	65
4.2	Assessment of postural kinematic synergies (Donders' law): experimental setup and protocol	66
4.2.1	Inverse optimization to capture experimental postural kinematic synergies	67
4.3	Results	72
4.4	Conclusion	76
5	Assessment of Postural Muscular Synergies	79
5.1	Introduction	79
5.2	Materials and methods	80
5.3	Results	85
5.4	Conclusion	86
II	Movement	89
6	Effects of Mechanical Impedance (joint stiffness and damping) on Wrist Movement	91
6.1	Introduction	91
6.2	Methods	92
6.2.1	Donders-fitted λ_0 -PMP	92
6.3	Comparative analysis of task-dynamics: experimental pointing tasks vs Donders-fitted λ_0 -PMP model predictions	94
6.3.1	Experimental protocol and data analysis	95
6.3.2	Results	96
6.4	Conclusion	98
7	Conclusion and Outlook	105
7.1	Major contributions	106
7.2	Ongoing & Future works	107
7.2.1	Is there any 'biomechanical intelligence' behind human null-space motions?	107
7.2.2	Task-space Separation Principle & Motor Cortex	109
7.2.3	Force Fields Learning, Proprioception and Sensory Integration: Why Does Donders' surface drift?	110
7.2.4	Biomechanics and Control of Human Wrist During Contact Tasks	111
	Bibliography	114

Abstract

The apparent conflict between posture and movement, especially in the presence of redundant degrees-of-freedom (DOF), resulted in mutually-exclusive theories and models of human motor control and, to date, a unifying picture of how the brain manages to control both posture and movement is still lacking. In presence of kinematic redundancy, i.e. whenever multiple postures are available to satisfy a given task constraint, numerous experimental studies highlighted the existence of *postural synergies*: on average *humans adopt a unique posture for a given task constraint*. Several computational models have shown that postural synergies can be predicted via (local) constrained optimization of posture-dependent cost functions. However, often, these models are static and unable to predict movement generation. Differently, computational models capturing human-like movement features, such as straight-line hand paths and bell-shaped velocity profiles, have been traditionally formulated according to the optimal control framework. As such, these models usually lead to path-dependent terminal postures (i.e. at the end of the movement) and therefore are unable to capture postural synergies. This thesis proposes the *Task-space Separation Principle* and a general computational framework for posture and movement planning for redundant manipulators. The problem of kinematic redundancy is framed as a constrained optimization problem, traditionally solved in robotics via the method of Lagrange multipliers (LM). It is shown that LM act as task-space force fields that in general can be separated into a static (configuration-dependent) component responsible for postural control and a dynamic (velocity-dependent component) responsible for movement planning, leading to a novel extension of the *Separation Principle* previously proposed in human motor control literature. In particular, by generalizing the dynamic force field to any task-space force field policy, it is shown that the proposed approach generalizes and extends several computational models proposed in robotics as well as in neuroscience. The proposed framework is applied to the (redundant) task of pointing with the human wrist and it is shown that it can capture the experimental motor strategies (i.e. both posture and movement features) displayed by human subjects.

Chapter 1

Introduction

1.1 Motivation & Objective

Simple motor acts such as drinking from a cup of coffee or handing-over an object to a friend require the coordination of redundant degrees-of-freedom (DOF) via the selection of suitable postures and movements. Motor redundancy allows humans to flexibly and robustly perform motor tasks. However, it also poses a ‘challenge’ for the brain as infinite postural configurations and muscle activations are available to satisfy the same task requirement. In addition to motor redundancy, our brain must also cope with the apparent conflict between posture and movements. Postures are (static) equilibrium positions of one or several body segments with respect to other segments or with respect to space that are stabilized against external perturbations [1]. Movement, on the contrary, is in apparent contrast with the very definition of static equilibrium. It is a temporary equilibrium-breaking between internal and external forces/torques that ultimately reconfigure the body in a novel stable posture. How the brain manages to solve motor redundancy and the posture/movement problem is still debated in neuroscience. The dichotomy between posture and movement has very often resulted in mutually-exclusive theories and models of human motor control (i.e. *posture-based models* and *movement-based models* [2, 3]) so that to date a unifying picture of how the brain may control both is still lacking [4].

The *motor synergy hypothesis* for example, has been proposed as a possible simplifying strategy that the brain adopts when facing redundant tasks. By grouping multiple control variables into synergies, the brain reduces the number of DOF effectively available to solve a certain task [5, 6, 7]. This *dimensionality reduction* has been observed both at the kinematic level (*kinematic synergies*) [8, 9, 10, 11, 12] and at the muscular level (*muscular synergies*) [13, 14, 15] and during both the execution of movement and the maintenance of posture [16].

The essence of postural kinematic synergies is that the equilibrium body

configuration adopted to satisfy a given task constraint only depends on the task constraint itself and it is therefore independent from the movement history and/or the initial body configuration. From a computational perspective, these synergies can be predicted via (local) constrained optimization of postural-dependent cost function. If on the one hand this approach leads to unique constrained optimal posture, on the other hand it does not solve the problem of movement generation. The Equilibrium Point Hypothesis (EPH) is a well-known posture-based approach to human motor control positing that movements are achieved by gradually shifting the equilibrium position of each joint from the starting to the ending position [17]. While the EPH proposes a solution to the posture/movement problem, it does not explicitly address the kinematic redundancy problem [18], i.e. it is not clear how the brain might determine postures by explicitly computing the corresponding equilibrium points. Another approach is the so-called Passive Motion Paradigm (PMP) [19, 20, 21] that can be considered a computational generalization of the EPH, in that goals and kinematic constraints can be superimposed when viewed as force-fields. First proposed in the 80s [19], the PMP has evolved over the years as an alternative framework to optimal control theory and has been applied to human motor control as well as to motion planning for humanoid robots [21]. One of the major strengths of the PMP lies in its computational simplicity. However, as shown in Chapter 3, the PMP only partially solves the posture/movement problem as in general postural control strategies interfere with movement strategies.

Stereotypical movement features [22], such as (approximately) straight hand paths and bell-shaped velocity profiles can be predicted with optimal control frameworks (movement-based models). Although this approach has been very successful at modelling movement strategies typical of planar non-redundant point-to-point reaching movements [23, 24, 25, 26], some computational studies have reported difficulties in solving optimal control problem in the presence of both kinematic redundancy and static force fields due for example to gravity. This is because, to hold the body still at equilibrium (i.e. at the end of a movement), suitable boundary conditions must be specified so that the optimal muscle forces can counterbalance the static forces acting on the body (see [18] and references therein). Recently this problem has been tackled with the *Separation Principle* according to which the brain processes static (i.e. configuration-dependent) and dynamic (i.e. velocity-dependent) joint torques separately [27, 28, 18]. By combining the optimal control framework with the Separation Principle, Guigon and colleagues were able to implement human-like motor strategies in redundant manipulators and robots [18, 29]. Nevertheless, by applying the optimal control framework and the Separation Principle at the joint-space level results into path-dependent (i.e. dependent on the movement history and initial body

configuration) terminal postures and therefore such an approach cannot predict kinematic synergies.

The main objective of this thesis is to develop and validate a general, unifying and bio-inspired computational framework for human-like posture and movement planning with a specific focus on posture and movement strategies typically observed in humans during redundant pointing tasks performed by means of wrist and forearm rotations. Despite this biomechanical complex is quintessential for any daily manipulation task, little is known on how the brain coordinate these DOF [30].

By framing kinematic redundancy as a constrained optimization problem and by solving it with the method of Lagrange multipliers (LM), the first contribution of this thesis is to show that LM act as task-space force fields that in general can be *separated* into static and dynamic force fields. Hence, by applying the Separation Principle to LM, this thesis tackles the posture/movement problem via the *Task-space Separation Principle* according to which the brain may plan posture and movement via the superposition of *static* (or configuration-dependent) *task-space* force fields responsible for postural control and dynamic (or velocity-dependent) *task-space* force fields responsible for movement planning. In addition, it is shown that several task-space force field policies, previously proposed in the literature, are possible for the implementation of the dynamic force field responsible for movement. Therefore, the proposed approach is general and unifies and extends several theories and models of neuroscience and robotics, among which: kinematic postural synergies [22], the Passive Motion Paradigm [19, 20, 21], the velocity resolution control [31] and the optimal control framework [26, 18]. Lastly, the proposed computational framework is validated with human experiments and simulations involving redundant pointing tasks performed by means of wrist and forearm rotations.

1.2 Thesis outline and contribution

Chapter 2 contains a review of human motor control at the experimental and computational level with particular emphasis for kinematic redundancy and the posture/movement problem.

In Chapter 3 kinematic redundancy is framed as a constrained optimization problem solved with the method of Lagrange multipliers (LM). It is shown that LM act as task-space force fields, the Separation Principle is used to separate LM into static and dynamic force fields and, to develop a general computational model for posture and movement planning in redundant manipulators.

Chapter 4 begins with a description of the experimental setup used to assess human wrist pointing strategies. The experimental results, in particular human

postural strategies, are then used to estimate via a novel and efficient non-linear inverse optimization approach, the model parameters responsible for postural control.

Chapter 5 presents a preliminary experiment in which subjects perform an isometric wrist pointing tasks designed with the aim of identifying if there is any relationship between kinematic postural synergies (such as Donder's law), wrist torque variability and muscular synergies. By comparing joint torque variability with the extracted muscle synergies it is shown that, in this scenario, the brain controls wrist muscles synergistically rather than flexibly [32, 33], hence confirming previous experimental findings [34].

Chapter 6 focuses on movements during redundant wrist pointing tasks. More specifically, experimental movement strategies are compared with those predicted by the λ_0 -PMP model presented in chapter 3. The main hypothesis is that a Donders-fitted λ_0 -PMP model (see chapter 4), i.e. fitted to only capture postural strategies, is also able to display path dynamics such as curved task-space trajectories as experimentally found by Charles and Hogan [35].

Chapter 7 contains a summary of the main contribution of this thesis together with an outlook on future works.

Chapter 2

Background: Posture, Movement & Redundancy

2.1 Introduction

Simple motor acts such as drinking from a cup of coffee or handing-over an object to a friend require the coordination of redundant degrees-of-freedom (DOF) via the selection of suitable postures and movements. If on the one hand motor redundancy allows humans to flexibly and robustly perform motor tasks, on the other hand it poses a ‘challenge’ for the brain as infinite postural configurations and muscle activations are available to satisfy the same task requirement. In addition to motor redundancy, our brain must also cope with the apparent conflict between posture and movements. Postures are (static) equilibrium positions of one or several body segments with respect to other segments or with respect to space that are stabilized against external perturbations [1]. Movement, on the contrary, is in apparent contrast with the very definition of static equilibrium being a temporary equilibrium-breaking between internal and external forces/torques that ultimately reconfigure the body in a novel stable posture¹. In other words, “movement is performed against a background of subtle postural adjustments” [37].

Next sections review the main theories and models that have proposed in an attempt to explain how the brain solves motor redundancy as well as the apparent paradox between posture and movement.

¹Note that in human motor control several possible definitions of posture and movement. See [1, 36] for more details.

2.2 Motor redundancy and the degrees-of-freedom problem

The *degrees-of-freedom problem* was firstly introduced by Bernstein [5] and nowadays, both roboticists and neuroscientists, recognize that motor control involves a sequence of (increasingly) redundant coordinate transformations [38, 39]. As shown in the example of Fig. 2.1, the acquisition of extrinsic (or task-space) requires the coordination of hand posture and movement that in turn requires the coordination intrinsic variables such as joint rotations and muscle activations. Because we live in a 3D world, motor goals require at most six variables to be specified: three coordinates indicating the goal position and three coordinates indicating the goal orientation with respect to the body. However, the human body is a complex kinematic chain with more than 300 kinematic DOF actuated by more than 600 muscles [40]. If on the one hand this abundance of motor variables makes the human body one of the most dexterous and flexible kinematic chains of the animal kingdom, on the other raises the question: how does the brain choose which limbs, joints and muscles to move in order to solve a given motor task?

Motor goals are sensed through internal feedback and the interplay between visual auditory and proprioceptive feedback let the brain estimate the spatial position and orientation of the body with respect to its environment and goals. With reference to Fig.2.1, once a motor goal has been selected and the relative configuration between body and goals has been established, the brain must decide which path the body should follow. Furthermore, the brain must choose at which speed the body should move. In other words the brain has to find a specific trajectory out of an infinite number of possible paths and velocities (see Fig.2.1). The spatial trajectory then, must be transformed into a sequence of joint rotations together with a sequence of muscle activations that will ultimately lead to the desired goal [41]. As we shall see in the next sections, this sequence of hierarchical and serial transformations is not shared by all theories and models proposed in neuroscience (see for example [26]). However, it provides a framework to understand, compare and explain in what these theories differ from one another.

2.3 Kinematic constraints and synergies in humans

2.3.1 Empirical motor laws

Despite the enormous amount of DOF that the brain has to cope with for every motor act, and despite each human has his/her own biomechanical param-

Figure 2.1: An example of goal-directed posture and movement planning during a redundant motor task. Desired task constraints/goals are in general not sufficient to uniquely specify how to coordinate individual joints and muscles. The many DOF afforded by the joints (three in this example) and muscles (eight in these example) allows for multiple (i.e. redundant) solutions. In general, the brain has to solve a hierarchical sequence of increasingly redundant transformations (from hand posture and movement to muscle activations). However, notice that this hierarchical sequence of coordinate transformation for planning and controlling posture and movement is not shared by all human motor control theories [26]. Image readapted from [42].

eters (link lengths, body weights, muscular strength,...), studies have revealed stereotypical postural and movement features that are invariant across subjects and experimental conditions (see [22] and references therein). Movement duration has been shown to be function of the ratio between the distance to the target and the target size (*Fitts' law*), i.e for the same target distance humans execute slower movements if higher accuracy (smaller target) is required. Hand-writing studies have revealed that there is a precise relationship between the path curvature traced by the hand and hand speed. In particular, the higher the curvature the slower the movement (*two-thirds power law*). Point-to-point movements, whether periodic or not, have a duration that does not depend on the distance, i.e. short movements are executed slower than long-distance movements (*isochrony principle*). During planar point-to-point reaching movements, the hand features roughly straight-line path and symmetric bell-shaped velocity profiles (*maximum-smoothness principle*). Deviations from straight-line paths have been observed in several conditions while bell-shaped velocity profiles seem to be an *invariant* feature that repeats across subjects, load and speed conditions [28]. *Trajectory constraints* interrelate temporal aspects with geometric aspects of

movements and several evidences suggest that they have a neural origin and hence are not due to biomechanical constraints [22].

2.3.2 Postural constraints: Donders'law

The motor synergy hypothesis has been proposed since Bernstein [5] as a possible solution to the redundancy problem. By grouping multiple control variables into synergies, the brain reduces the number of DOF effectively available to solve a certain task [6, 9]. A well known postural kinematic synergy (or kinematic constraint) is Donders'law: a stereotypical coordination of the redundant DOF associating a unique posture to a given task. The name of the law comes from the Dutch ophthalmologist Franciscus Cornelis Donders (1847) who was the first to show that for any steady gazing direction (*task*), the human eye assumes the same combination of elevation, azimuth, and torsion angles (*posture*). Two decades later, Listing and Helmholtz found that, when the head is fixed held upright and the eye gaze to distant targets, Donders law specialises in the so called Listing law: all possible eye orientations can be realised by starting from a reference position (so called *primary position*) and by a single rotation about an axis lying in the Listing plane (that is orthogonal to the gaze direction in primary position) [8].

Donders' law is known to hold robustly (in a statistical sense) for eye, head, wrist movements during gazing or pointing tasks [43, 44, 45, 46], while contrasting evidence exists for arm movements [3, 47, 10, 48]. Although, a recent study by Ewart et al. seems to reconcile previous contrasting results [48]. They showed that the variability of terminal posture arising from different starting position is not statistically different from the variability of the terminal posture reached from the same starting position and therefore they concluded that, by taking into account intrinsic motor variability, Donders' law applies also to unconstrained and visually guided reaching movements.

The typical way Donders' law is assessed and quantified is via numerical fitting of experimental data. The motor space for eye, head and wrist (functionally including the forearm DOF) is usually considered as a 3 DOF, purely rotational space. Eye/head/wrist postures correspond then to 3D rotations and are usually encoded as points of a 3D space, generally expressed in different coordinates such as quaternions, rotation vectors, or Euler angles. Tasks such as gazing/pointing at targets on a screen are two-dimensional but involve three DOF movements, therefore leading to a redundant problem. Existence of a DL is typically demonstrated by showing that a cloud of points (each encoding a 3D posture of eye, head or wrist while gazing/pointing at a set of targets on a screen) can be fitted to a (Donders') surface, in the 3D space of postures. Similar procedures can be applied to the human arm which, however, requires more care

in specifying the task, as the arm could be fully extended [49, 10] or with a flexed elbow [47] (see Fig. 2.3.(b)) as well as to the lower limb where, during walking, it has been shown that three leg segments (foot, thigh and shank) are constrained to covary along a (Donders) plane [11].

A peculiar feature of Donders' law is that it is *volatile*, *flexible* and *adaptive*, hence a 'soft' constraint of neural origin.

Donders' law is *volatile* in the sense that, although evidence of DL can be found in different experimental scenarios, *violations* of DL have also been reported in specific situations, especially when it comes to the human arm [50, 51, 52] or for the eye when instructions to move as fast as possible are given to subjects [8]. For the human wrist, subject-specific Donders' surfaces, found during free pointing, disappeared whenever subjects were attached to a 3D mechanism, assuming a shape typical of locked mechanisms (gimbals) [12].

The evidence gathered in various domains and scenarios suggests that the brain implements Donders' law as a *flexible* family of *holonomic constraints*, neurally modulated under some form of *velocity control* [47, 44] to solve redundancy as well to implement some *optimality* purpose which might vary based on experimental scenarios and physiological conditions [47, 45, 53]. For the human eye, the primary function is vision. As we gaze around, the brain receives images of the world with a certain amount of *torsion*, Donders' law precisely assigns a *unique* torsion for each gazing direction. In other words, *torsion is path-independent*, a direct consequence of the holonomic nature of Donders' law. Ensuring a path-independent torsion not only makes life simpler for the brain from a computational point of view (imagine if, when gazing straight ahead, the image on our retina appeared rotated differently and every time, depending on the previous paths of our gazing) but also prevents ending, painfully, with our eye balls tilted upside down due to *accumulation of torsion*, after gazing along a closed loop. This issue is well known to roboticists since the 80s as *the problem of non-repeatability* affecting redundant manipulators [54, 55, 31] (see Fig. 2.2).

Depending on the particular context, the brain is capable to switch and select different holonomic constraints or Donders' laws. Ceylan et al. [45] showed that the motor strategy controlling head movements can be switched between Listing-like Donders and Fick-gimbal-like Donders during redundant pointing tasks (see Fig.2.3.a). In particular, during head-eye gaze shifts, when the head serves just as a base for eye gazing the Fick-gimbal strategy is used. In this case the head has a minor role over gazing shifts (mainly under eye control) and therefore it optimizes movements under different constraints (such as the work done against gravity). On the other hand, by forcing the head to act as the primary pointer for gaze shifts (subjects in this case wore pinhole goggles), the most efficient strategy seems again to be the Listing strategy which produces quick head

Figure 2.2: Examples of holonomic (a) and nonholonomic (b) solutions to the inverse kinematic problem. While forward kinematics (FK) is well defined in both cases, only the holonomic case allows identifying an inverse kinematics solution via Donders law. In addition, holonomic constraints (a) guarantee repeatable solutions, i.e. closed paths in task-space correspond to closed paths in joint-space. In general, non-holonomic constraints (b) lead to non-integrable solutions, i.e torsion accumulation.

orientations using the smallest possible rotation (about a fixed axis in the Listing's plane) toward and away the reference position (primary position).

Similar synergies and switches have been shown to be consistent with the upper arm control during redundant pointing tasks [47]. In this case, when the arm is fully extended, the shoulder has the role of primary pointer and hence adopts a Listing strategy. Nevertheless, this strategy is switched in a Fick-gimbal strategy when the forearm is bent in an inverted pendulum configuration. In this case the Fick strategy optimizes the arm postures so as to minimize the work done against gravity (see Fig.2.3.b).

Lastly, Donders' law appears to be *adaptive*, with important clinical implications for the assesment of phisiological motor control [53, 11].

2.4 Computational approaches to human motor control

2.4.1 Optimality-based approach and Separation Principle (joint-space)

A possible explanation to the stereotypical pattern observed in human motor control is that the brain, when planning and/or controlling movements, optimizes some performance criteria (or cost functions) that in turn lead to a unique solution to the redundancy problem. An open question in motor neuroscience is

Figure 2.3: Donders' law as a flexible postural constraint. Each surface represents a Donders synergy (or surface) and is obtained by fitting, in each scenario, the rotation vectors relative to head (a) and shoulder orientation (b). (a) Head pointing tasks executed under different experimental conditions: head-free gazing task (CT); wearing modified goggle that allows only partial vision through a single pinhole (GT). Donders' law (or Donders'surface) switches from a Fick-gimbal strategy (CT) to a Listing strategy (GT). Image adapted from [45]. (b) Pointing tasks executed with the shoulder while constraining the elbow at different angles with respect to the upper arm. When the arm is fully extended the brain adopts a Listing's strategy that switches to a Fick-gimbal strategy when the forearm act as inverted pendulum. Image adapted from [47].

to what extent movements are planned in extrinsic or intrinsic spaces and therefore, whether the brain optimizes kinematic (posture, velocity, accelerations, jerk) or dynamic variables (forces, torques or muscle activations). For instance, the *minimum-jerk* model [23], formulated in extrinsic space, predicts straight-line hand trajectories and bell-shaped velocity profiles. However, a limitation of the minimum-jerk model (and more in general of extrinsic motion planning) is that it requires inverse kinematics to convert the optimal hand trajectory into joint trajectories and therefore it does not solve the redundancy problem. Dynamic models are formulated directly in intrinsic space thereby minimizing an intrinsic effort related to joint torques [24, 52] or muscle tension [56]. They make no distinction between planning and execution and therefore kinematic trajectories (hand and joint trajectories) are considered an epiphenomenon of the intrinsic optimization of dynamic variables. These models are usually framed as constrained optimal control problems and determining suitable boundary conditions can be problematic in the presence of redundancy [3, 18].

Stochastic Optimal Feedback Control

The original optimality-based models proposed in neuroscience left out two important aspects of motor control: *signal-dependent motor noise* and *feedback* [25, 26]. Differently from motors used in robotics, biological actuators produce forces whose variability increases proportionally to the level of the driving motor command [25]. During redundant tasks, motor noise is not uniformly distributed but seems that the brain keeps it at a minimal level only for those directions that would interfere with the current task. Higher level of variability are instead found in the null-space directions, i.e. those that interfere with the task [6]. A feature of human motor control that has lead to the so called *UnControlled Manifold* (UCM) hypothesis [57].

The stochastic optimal feedback control (SOFC), formulated according to the *minimum intervention principle* (errors that do not interfere with the task are not corrected) and the concurrent minimization of extrinsic errors and intrinsic efforts [26] is nowadays one of the most accredited theory of motor control. It can predict both average trajectories and motor variabilities similar to those measured in different experimental scenarios [58]. It does not require a planning stage: trajectories are the result of the optimization process based on the (estimated) sensory feedback and the desired motor goal.

A big challenge for SOFC is the *curse of dimensionality*, i.e. the computational burden arising from models involving several DOFs. To overcome this difficulty Todorov and colleagues [59] have proposed a hierarchical framework that generates ‘approximately’ optimal solutions. Central to the framework is the introduction of a low-level controller that is optimized in order to do not interfere

with the desired task-space dynamics which are generated and optimized via the high-level controller.

The concurrent minimization of errors and efforts, if on the one hand avoids the use of terminal constraints, on the other hand has been criticised because this type of cost function does not provide a unique description of human motor control [18]: changing the relative contribution of errors and efforts affects model prediction [18].

Separation Principle (joint-space)

Experimental evidence shows that many kinematic features typical of human movements are invariant across different subjects, different hand-held load conditions and different movement speed. It has therefore been hypothesized that the human brain processes static (or configuration-dependent) and dynamic (or velocity-dependent) force fields separately [27, 28, 60, 61]. Because static forces such as gravitational or elastic fields are predominant during slow movements and are not affected by movement speed, the Separation Principle [18] has been proposed as a simplifying control strategy for the brain to learn new movements [60], to efficiently time-scale arm trajectories [27, 28] and to robustly cope with the effect of gravity in different environments [61].

When an optimal control approach is used to solve kinematic redundancy in the presence of configuration-dependent potential (such as gravity or joint elasticity), suitable boundary conditions must be specified in order to reach the desired terminal equilibrium. In other words, maintaining a desired final position requires to compensate for the intrinsic torques arising from the configuration-dependent potentials. It has been argued that if such a problem is addressed by means of cost functions that penalize terminal postures away from a desired equilibrium position, then, the solution of the optimal control problem would depend on the nature of the static forces and therefore incompatible with experimental observations [18].

To overcome this issue, Guigon et al. reformulated the Optimal Feedback Control Framework, at the joint-space level, by splitting joint control torques into two different contributions:

$$\boldsymbol{\tau}(t) = \boldsymbol{\tau}_{dyn}(t) + \boldsymbol{\tau}_0(t) \quad (2.1)$$

where $\boldsymbol{\tau}_0(t)$ is the joint space torque that compensate all static effects (such as due to gravitational or elastic potentials) and $\boldsymbol{\tau}_{dyn}(t)$ is the solution to the optimal control problem in the absence of static torques [18].

If on the one hand this reformulation of Optimal Feedback Control can produce invariant movement features that are not affected by static torques, on the

other hand it predicts terminal postures that depends on the initial configuration [18] and therefore it is not compatible with Donders'law.

Remark:local vs global optimization and Donders'law. The holonomic nature of Donders'law, i.e. that the terminal posture is path-independent, can be captured by constrained optimization, as shown for example for the human wrist [62, 63] and the upper limb [64]. Given an intrinsic (i.e. defined in joint-space) cost function one can find the unique optimal posture that satisfy a given task (constraint). The cost function could be either a physical potential due, for example, to gravitational or elastic joint torques, or a virtual potential such as a discomfort function penalizing postures too close to joint limits [65, 62, 66]. Models that capture Donders' law are also called *Posture-based* models [2, 3, 67]. These type of models, based on a local optimization of an intrinsic cost function, do not address movement generation, i.e. which trajectory to follow when moving from a starting position to a terminal one. Differently, optimal control models for the generation of movements, are usually formulated following a global optimization approach, i.e. the cost function is minimized along the entire trajectory. The trajectories predicted by this models are usually path-dependent (the solution depends on the movement history) and therefore cannot predict Donders' law. This type of models are usually called *transport-based* or *trajectory-based* models [2, 3, 67].

Posture-based and trajectory-based models have been compared by Admiraal and colleagues [3] during pointing and reaching movements. They concluded that: "*a strict distinction between posture-based models and trajectory-based models is an oversimplification.*".

In summary, it is highly debated to what extent optimality principles apply to human motor control [68, 21] and whether the brain uses a global or a local optimization strategy [69].

2.4.2 The cybernetic approach: motion planning with internal models

The engineering tradition has mostly developed around two main fundamental concepts: linearity and low noise. On the contrary, biological systems are highly non-linear systems constantly interacting with internal and external noisy states [70]. In addition, biological signals are transmitted at a much lower rate (up to 150ms [71]) than in conventional robotic architectures (1-2 msec). In control theory it is well known that delay drastically impact the stability of closed-loop the system. Similar to robust and adaptive control proposed in control engineering and robotics [72], *internal models* have been proposed as central building blocks of human motor control [73]. Like a Kalman filter, *forward models* act as sensory predictor that anticipate the consequences of the current motor action. They are used to overcome noisy and delayed sensory feedback. They are also

a key element in the theory of SOFC [26]. Computational models based on distinct planner and executer modules, often need an inverse model for the correct generation of the motor plan. The planner generates kinematic desiderata (position, velocities and accelerations) that are transformed into control torques or muscle activations by the executer. However, limb dynamic is subject to inertial, viscous and environmental (non-linear) forces that most often act against the planned action. Therefore, a simple feedback controller (such as a proportional-integral-derivative) is not sufficient to ‘perfectly’ track the desired plan. For a given desired trajectory then, *inverse models* generates the feed-forward motor commands that compensate for all the generalized forces that would interfere with the planned motion. Internal models are thought to be implemented by the cerebellum and nowadays are central to the theory of motor learning and motor adaptation to visuo-motor rotations and force fields during both dynamic [74] and isometric conditions [75, 76, 77]. By analysing motor strategies that human implements when interacting with novel and unstable tasks, Franklin and colleagues [78, 79] have proposed a computational model that integrates internal models with impedance control demonstrating how stiffness adaptation during different phases of learning is an important aspect of human motor control.

Despite the popularity and the vast range of experimental scenarios in which internal models seem to play a crucial role for the correct execution of movements, their biological validity has been debated for a long time [80].

2.4.3 Motion planning with equilibrium points and force fields

Humans are capable of ‘freezing’ the body in different positions or equilibrium postures whereby the sum of muscle-generated forces balances all the external forces acting on the body. When additional external forces perturb such equilibrium body configuration, muscles’ spindle sense muscle deformations and transmit this information to alpha motoneurons that eventually increase their activity so as to compensate the external perturbation [81]. This negative feedback control is called stretch reflex and is central for postural stability. How does voluntary movement control is achieved with such a mechanism in place? That voluntary control from the central nervous system inhibit such a mechanism is a hypothesis that was rejected long time ago, as this mechanism have been shown to be active also during volitional motions [80]. To solve this *posture-movement paradox*, Von Holst and Mittelstaedt proposed the ‘Reafference Principle’ [81].

According to this principle, every time the central nervous system (CNS) specifies descending motor command (or *efference*) to the muscles, it also forms a ‘copy’ of it called *efferent copy* (or *corollary discharge*). The proprioceptive feedback coming from the periphery to the CNS is instead the sum of two contributions: the *reafference* feedback is the one that the CNS predicts given the current mo-

tor command, the *exafference* feedback instead, arises from external and unpredictable perturbations. The error between the efference copy and the proprioceptive feedback let the CNS distinguish between self-generated motions (zero error) and external perturbations (positive/negative error)[81, 82]. This feedback mechanism and the concept of efference copy is also central for the internal model theory [71]. It would explain not only the posture-movement paradox but can for example explain why voluntary rotations of head and eyes do not result into a 'rotate perceived world' [71].

The Equilibrium-point Hypothesis

The theory of internal models essentially sees the CNS (more specifically the cerebellum) as a 'multi-body dynamic simulator' that transforms desired kinematic plans into motor commands encoding desired joint and/or muscular torques and force (inverse dynamics) [71]. So, according to the internal model theory, motor commands from the CNS to motoneurons encode generalized forces [80]. However, this type of signal is believed to be incompatible with the EMG signals recorded during isotonic movements (i.e. executed against constant, or more simply zero, resistance). It has been shown that when the arm is supported against gravity and the elbow is moved (in the horizontal plane) from an initial to a final configuration, at the end of the movement the EMG signals of both agonist and antagonist muscles return to a similar activation level recorded in the initial position [80]. If agonist and antagonist were activated according to desired force levels, then, at the end of the movement, agonist muscles would be still active to compensate for the elastic force arising from the antagonist muscle [80, 83]. This inconsistency has been addressed with the Equilibrium-Point Hypothesis (EPH) that considers spinal reflexes and muscles as a spring-like system that generate forces according to Hooke's law: $K(\theta_d - \theta)$. By *resetting* the *threshold activation* level θ_d the CNS can change the equilibrium-position at which muscles become 'silent'. External perturbations stretching the muscle away from θ_d would generate a restoring force [80, 83]. According to the EPH, motion is merely a continuous shift of equilibrium postures also called a *virtual trajectory*[84, 85]. Furthermore, the CNS does not need internal models nor does it compute detailed inverse dynamics and therefore, the real trajectory $\theta(t)$ usually differs from the virtual (planned) one $\theta_d(t)$. The EPH has been used together with the minimum-jerk model to explain point-to-point planar reaching motion executed with shoulder and elbow [23]. It can account for straight-line hand paths and bell-shaped velocity profiles. However, it has been noted that, good tracking of the virtual minimum-jerk trajectory require high level of stiffness that are not compatible with those experimentally measured in the same conditions [86]. Alternatively, the same motions could be achieved with lower level of stiffness but by planning

complex virtual trajectories and therefore making the framework less computationally attractive [86, 71].

The Passive Motion Paradigm (PMP)

Internal models theory and EPH have been considered mutually exclusive theory of motor control for a long time [80]. The Passive Motion Paradigm (PMP) [19, 20, 21], shown in Fig. 2.4, bridges the gap between the two approaches by proposing a framework based on an *internal simulation process* that extends the EPH. As in the EPH, muscles, as tunable springs capable of storing and releasing potential energy, are central for the PMP framework to solve the redundancy problem. However, in the PMP framework, force fields rather than postures are the variables that control both postures and movements. Planning with force fields is attractive for two main reasons: 1) multiple constrained tasks can be executed through the superposition (or algebraic sum) of multiple force fields; 2) For redundant motor control problem formulating motor plan in terms of forces rather than kinematic variables is advantageous because, the mapping from task to intrinsic space is not ill-posed[19]. The main unit of the PMP framework is the *kinematic network* (also called internal simulation process or body schema), that distributes intrinsic and extrinsic force fields two each joint of the kinematic chain. The kinematic network is a non-linear differential equation whose main components are reported in eq. 2.2 and Fig.2.4:

$$\begin{cases} \tau_{extr} = J^T K(x_d - x) & (2.2a) \\ \dot{q} = W^{-1}(\tau_{extr} - \nabla_q h) & (2.2b) \\ x = \int J \dot{q} dt. & (2.2c) \end{cases}$$

Motor goals (or extrinsic constraints) are coded with the metaphor of *virtual springs* (virtual because simulated by the kinematic network) that attract the end-effector proportionally to the distance between the goal and the end-effector ($F = K(x_d - x)$). This field is then mapped in joint-space (through the Jacobian transpose) (2.2.a) where, after being superimposed to intrinsic force fields ($\nabla_q h$) is converted into joint velocities via the admittance matrix W^{-1} (2.2.b). Lastly, from joint space velocities, the current end-effect position is estimated via (2.2.c) and used to update the task-space virtual field and the evolution of the network. To eliminate the dependency of the end-effector's speed from the task-space stiffness (K) and the admittance W^{-1} , a time-dependent gain matrix (not shown in the previous equations) is introduced in the kinematic network to regulate the speed of the movements [21].

The admittance matrix (mimicking a sort of joint viscosity) regulates the dis-

Figure 2.4: The Passive Motion Paradigm: mechanical equivalence and computational schema. The different colors highlight the two possible implementations that differ by the presence or not of the intrinsic elasticity responsible for postural kinematic constraints[19, 87, 21].

tributions of the various fields to each joint of the chain and therefore different values of W^{-1} capture different *synergistic* joint activations. For instance a joint can be completely ‘frozen’ by setting the corresponding elements of W^{-1} to zero while the intrinsic constraint $\nabla_q h$ mimics muscle intrinsic elasticity that keeps the kinematic chain away from joint limits.

The framework is labelled *passive* because in a kinematic network joint trajectories are not explicitly pre-computed but are the result of a non-linear dynamical system that evolves according to intrinsic and extrinsic constraints (or force fields) imposed on the kinematic chain. Fig. 2.4 shows a mechanical equivalent and a computational schema of the PMP, in particular its viscous (without intrinsic elasticity) and visco-elastic implementation. As shown in section 3.3.5, the former implementations does not capture Donders’ law, while the latter does not solve the posture/movement problem i.e., the intrinsic elasticity responsible for postural control interfere with the extrinsic Cartesian spring responsible for movement.

Remark: PMP vs Optimal Control. The main critiques to the optimal (feedback) control as a theory of human motor control are summarised in the following [21, 58]: i) different cost functions can qualitatively predict the same set of experimental data and therefore the type of specific cost function is still debated; ii) optimal control models are difficult to solve, especially for high-dimensional non-linear systems. Although there have been several attempts to speed up such computations [59], most of optimal (feedback) control models are limited to simple planar tasks involving at most two DOF; iii) optimal control models offers

a powerful tool to analyse and understand *what* the brain does however much less is known about if and *how* the brain may implement such computations [88]. In this perspective, the PMP has recently been re-interpreted as an alternative to the optimal control framework and as a bio-inspired motion planner for both humans and robots. The *internal simulation process* of a kinematic network try to address not only *what* the brain does when planning posture and movement but also *how* it could be implemented into bio-inspired neural networks [89, 90].

Chapter 3

Task-space Separation Principle: a force field approach to posture and movement planning for redundant manipulators

3.1 Introduction

As reviewed in the previous chapter, Donders law is a holonomic constraint, probably neurally modulated under some form of velocity control [45, 47], that the brain implements to avoid torsion accumulation. In other words, Donders' law provides a solution to kinematic redundancy that is unique and path-independent. This feature of Donders' law is known in robotics as *repeatable* or *holonomic* solution to the inverse kinematic problem and has been a central issue since the '80s [92] (see Fig. 2.2). At the velocity level, the *velocity resolution control* has been proposed as a general framework for kinematic motion planning [31].

In this chapter the problem of kinematic redundancy is framed as a constrained optimization problem, traditionally solved via the method of Lagrange multipliers (LM) [31]. First, it is shown that LM act as task-space force fields leading to a novel task-space force formulation of the velocity resolution control framework. Then, it is highlighted that in general LM can be *separated* into a static (configuration-dependent) task-space force field, responsible for postural control (and Donders' law) and, a dynamic (velocity-dependent) task-space force field, responsible for movement. Hence, by applying the Separation Principle to

Part of the work presented in this chapter was published in [91]

these task-space force fields, the Task-space Separation Principle is proposed as a solution to the posture/movement problem. The Task-space Separation Principle is then employed for the formulation of a general computational framework for posture and movement planning in redundant manipulators that unifies and extends several theories and models of human motor control and robotics. The proposed framework is applied to the (redundant) task of pointing with the human wrist.

3.2 Lagrange Multipliers as Task-space Force Fields

Consider an n -dimensional, kinematically redundant manipulator with configuration vector (joint angles) $\mathbf{q} \in \mathcal{Q} \subset \mathbb{R}^n$ and an m -dimensional task-space $\mathbf{x} \in \mathcal{X} \subset \mathbb{R}^m$, with $m < n$, defined by a smooth forward kinematics:

$$\mathbf{x} = FK(\mathbf{q}) \quad (3.1)$$

A typical problem is finding a joint-space configuration $\mathbf{q}$ leading to a given desired task-space configuration $\mathbf{x}$, i.e. as in (3.1). For kinematically redundant manipulators, characterized by $m < n$, this is typically an under-determined problem as there often exist infinite joint-space configurations solving a given task. Due to nonlinearities, finding the analytical inverse to eq. (3.1) is in general not a viable solution. A typical approach consists of operating on a linearized problem, i.e. considering the relationship between task velocities $\dot{\mathbf{x}}$ and joint-space velocities $\dot{\mathbf{q}}$ via the *task Jacobian* J

$$\dot{\mathbf{x}} = \frac{\partial FK}{\partial \mathbf{q}} \dot{\mathbf{q}} = J \dot{\mathbf{q}} \quad (3.2)$$

where J is an $m \times n$ matrix and which, hereafter, shall be assumed of full rank, i.e. $\dim(J) = m$. Equation (3.2) can be interpreted as a kinematic constraint (i.e a given task-space velocity) applied at the end-effector.

In our previous works [62, 63], we performed a task-constrained minimization of a static cost function $h(\mathbf{q})$, analogous of an elastic potential, and this allowed for the determination of optimal postures among those compatible with a given task. However, this formulation only considers static postures and does not address movement. We shall now consider a dynamic cost function and consider the analogous of a *viscoelastic power* as this will also include velocities and determine optimal motions as well. Following [31], a unique and optimal solution for $\dot{\mathbf{q}}$ can be formulated as a constrained optimization problem:

$$\underset{\dot{\mathbf{q}}}{\operatorname{argmin}} \left\{ \frac{1}{2} \dot{\mathbf{q}}^T W(\mathbf{q}) \dot{\mathbf{q}} + \frac{dh}{dt} \right\} \text{ while } \dot{\mathbf{x}} = J \dot{\mathbf{q}} \quad (3.3)$$

where $W(\mathbf{q})$ corresponds to a positive-definite symmetric matrix for the joint-space velocities (defining thus a metric, or dot-product, for the space $\mathcal{Q}$) and $h(\mathbf{q})$ is posture-dependent cost function such as those previously shown to account for human postural control [65, 66, 64] and kinematic synergies [62, 63]. Similarly, the rate of change of the potential (i.e. power, in a mechanical analogy) $\frac{dh}{dt}$ can be rewritten via the gradient operator (i.e. a torque, in joint-space) as:

$$\frac{dh}{dt} = \nabla_{\mathbf{q}} h^T \dot{\mathbf{q}} \quad (3.4)$$

Formally, the original constrained-optimal problem can be formulated as an unconstrained optimization over an augmented state $(\dot{\mathbf{q}}; \boldsymbol{\lambda})$ of the following function

$$H(\dot{\mathbf{q}}; \boldsymbol{\lambda}) := \frac{1}{2} \dot{\mathbf{q}}^T W(\mathbf{q}) \dot{\mathbf{q}} + \nabla_{\mathbf{q}} h^T \dot{\mathbf{q}} + \boldsymbol{\lambda}^T (\dot{\mathbf{x}} - J \dot{\mathbf{q}}) \quad (3.5)$$

where $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \dots, \lambda_m]^T$ is the vector of so-called Lagrange multipliers (LM). Local minima or maxima of unconstrained problems can be determined by setting

$$\begin{cases} \nabla_{\dot{\mathbf{q}}} H(\dot{\mathbf{q}}; \boldsymbol{\lambda}) &= 0 \\ \nabla_{\boldsymbol{\lambda}} H(\dot{\mathbf{q}}; \boldsymbol{\lambda}) &= 0 \end{cases} \quad (3.6)$$

where $\nabla_{\dot{\mathbf{q}}} = \left[\frac{\partial}{\partial \dot{q}_1} \quad \frac{\partial}{\partial \dot{q}_2} \quad \dots \quad \frac{\partial}{\partial \dot{q}_n} \right]$ and $\nabla_{\boldsymbol{\lambda}} = \left[\frac{\partial}{\partial \lambda_1} \quad \frac{\partial}{\partial \lambda_2} \quad \dots \quad \frac{\partial}{\partial \lambda_m} \right]$ represent, respectively, the gradient operators over the joint velocities $\dot{\mathbf{q}}$ (n -dimensional) and over the vector of LM $\boldsymbol{\lambda}$ (m -dimensional).

Considering that terms such as $\nabla_{\dot{\mathbf{q}}} \dot{\mathbf{q}}$ and $\nabla_{\boldsymbol{\lambda}} \boldsymbol{\lambda}$ are just identity matrices (I_n and I_m respectively, n - and m -dimensional) and that $\nabla_{\boldsymbol{\lambda}} H(\dot{\mathbf{x}}; \boldsymbol{\lambda}) = 0$ simply returns the original constraint $\dot{\mathbf{x}} - J \dot{\mathbf{q}} = 0$, the general system of equations (3.6) can be simplified and rewritten as

$$\begin{cases} J^T \boldsymbol{\lambda} &= W \dot{\mathbf{q}} + \nabla_{\mathbf{q}} h \\ \dot{\mathbf{x}} &= J \dot{\mathbf{q}} \end{cases} \quad (3.7)$$

Remark [LM as task-space force fields]: It should be noted that, in eq.(3.7), if $h(\mathbf{q})$ represents a mechanical potential, for example due to gravity or elastic fields (e.g. generated by springs at each joint), then W can be interpreted as mechanical damping (e.g. friction at the joints) and the term $W \dot{\mathbf{q}}$ can be interpreted as *damping torque* (in the joint-space). For example in the case of a redundant manipulator, if $\dot{\mathbf{q}}$ and $\nabla_{\mathbf{q}} h$ can be interpreted as joint torques, so is the term $J^T \boldsymbol{\lambda}$ in the first of (3.7). The Jacobian matrix J not only maps joint velocities into task velocities, as in (3.2), but it also maps (via its transpose J^T) task-space forces into

If $h(\mathbf{q})$ is a mechanical potential, then $\frac{dh}{dt}$ denotes mechanical power and so does the term $\dot{\mathbf{q}}^T W \dot{\mathbf{q}}$, consistent with the fact that mechanical power can be written as the scalar product of velocities (transposed, $\dot{\mathbf{q}}^T$) with torques ($W \dot{\mathbf{q}}$)

joint-space torques and, therefore, *the vector of Lagrange multipliers λ is nothing but a posture-dependent force field in task-space.*

In traditional ‘velocity-resolution control’, the task velocity $\dot{x}$ is supposed to be known and this allows to uniquely determine the augmented state as function of the task velocity ($\dot{x}$) and joint torques $\nabla_q h$: from (3.7), since W is invertible, we can rewrite the first as $\dot{q} = W^{-1}J^T\lambda - W^{-1}\nabla_q h$ which substituted in the second gives $\dot{x} = JW^{-1}J^T\lambda - JW^{-1}\nabla_q h$, which allows to determine λ . Then, from the first of (3.7) one derives $\dot{q}$ as well:

$$\dot{q} = J_W^\# \dot{x} + (I_n - J_W^\# J)W^{-1}\nabla_q h \quad (3.8)$$

$$\lambda = B\dot{x} + BJW^{-1}\nabla_q h \quad (3.9)$$

where $J_W^\#$ ($n \times m$ matrix) is one of the possible *weighted generalized inverses* [93] satisfying $JJ_W^\# = I_m$, defined as:

$$J_W^\# := W^{-1}J^T (JW^{-1}J^T)^{-1} = W^{-1}J^T B \quad (3.10)$$

and:

$$B := (JW^{-1}J^T)^{-1} \quad (3.11)$$

represents the *Cartesian* damping as perceived in the task-space, whenever W is interpreted as joint damping, for example, for a mechanical manipulator. While equation (3.8) comprises many forms of velocity-resolution control, as highlighted by English and Maciejewski [31], to the authors’ knowledge, (3.9) has never been explicitly provided (albeit surely considered by other authors to derive (3.8)). The reason is that the vector of LM (λ) is usually considered as a dummy variable, while here we are going to stress its physical representation, as shown below.

3.2.1 Postural Control: Donders’ law from static task-space force fields and intrinsic potentials

Inspired by the Separation Principle, the Lagrange multiplier λ in (3.9) can now be rewritten as a composition of dynamic (λ_{dyn}) and static (λ_0) force-fields:

$$\lambda = \underbrace{B\dot{x}}_{\lambda_{dyn}} + \underbrace{BJW^{-1}\nabla_q h}_{\lambda_0} \quad (3.12)$$

The mechanical interpretation is straightforward, whenever W is regarded as joint damping of a manipulator:

- *Posture*: the static term λ_0 represents the (posture-dependent) task-space force necessary to block any effect in the task-space due joint torques $\nabla_q h$

while leaving the same joint torques free to act in the null-space. Leading to constrained-optimal postures.

- *Movement*: the dynamic term λ_{dyn} is the task-space force required to impose a velocity $\dot{x}$ onto the end-effector and overcome the Cartesian damping B . In other words, the task-space damping $B(q)$, in eq. (3.11), transforms task-space velocities $\dot{x}$ into task-space forces which balance out the effect of the dynamic force field λ_{dyn} , leading to the following task-space dynamic equation:

$$B(q)\dot{x} = \lambda_{dyn} \quad (3.13)$$

The postural effects of λ_0 can be seen during static task conditions, i.e. $\dot{x} = 0$, when the Lagrange multiplier reduces to its static component:

$$\lambda_0 = BJW^{-1}\nabla_q h \quad (3.14)$$

or alternatively, from (3.9), one obtains that $\lambda = \lambda_0$ whenever $\dot{x} = 0$, i.e. λ_0 is the value of task-space force λ to be applied to maintain the end-effector stationary ($\dot{x} = 0$) as shown in Fig.3.1. It should be noted that in a redundant manipulator one can have $\dot{x} = 0$ even if $\dot{q} \neq 0$. In other words, λ_0 blocks the effects of the torque $\nabla_q h$ on the task-space but leaves it unconstrained in the null-space allowing the manipulator to move towards a task-constrained minimum of the potential. This means that, once a potential function $h(q)$ is defined, *Donders' law can be conveniently captured by a static task-space force field λ_0* . Lastly, notice that the λ_0 force field, in eq. (3.14), in general depends on W . However, it is possible to show that, at equilibrium (i.e. when $\dot{q} = 0$), there is no such dependency, as the elastic torque $\nabla_q h$ has no null-space component and therefore the task-space projection is metric-independent. A condition that in robotics is known as *static consistency*, see [94] for more details.

The proposed task-space force field approach for posture and movement planning offers several advantages. The first advantage is that, the task-space has a lower dimensionality than the joint-space, in particular forces which live in the task-space (as opposed to torques in joint-space) naturally leave the null-space unconstrained. The second advantage is that, viewing postural control as a (task-space) force field leads to *generalization of velocity-resolution control framework*, as one can then ‘softly’ induce a Donders’ law without freezing the manipulator since additional *dynamic forces* λ_{dyn} can be superimposed and motion can be generated, either in accordance with the Donders’ constraint or away from it. This latter feature actually leads to the main advantage in terms of bioinspired control, i.e. the flexibility to comply with or to violate Donders’ law [3]. In our case, if the dynamic force field is exactly $\lambda_{dyn} = B\dot{x}$, then one obtains exactly eq.(3.9)

Figure 3.1: An example of (redundant) three DOF arm with elastic joints. The λ_0 task-space force field only compensates the task-space component (F_{el}) of the intrinsic elastic torques that would otherwise push the hand toward the resting posture q_0 . This task-space compensation, at equilibrium, leads to constrained optimal postures (Donders' law) that is, postures satisfying the desired task constraint while minimizing (in the null-space) the intrinsic potential.

as in the velocity-resolution control [31]. Nevertheless, next section will discuss possible generalizations of the model in terms of motion planning alternatives.

3.2.2 Task-space Motion Planning: a generalization

It should be noted that the system (3.7) and the equations (3.8)-(3.9) are equivalent (as the latter are solutions of the former) and can be combined as:

$$\dot{q} = W^{-1} \left(J^T (\lambda_{dyn} + \lambda_0) - \nabla_q h \right) \quad (3.15)$$

i.e highlighting that the problem of kinematic redundancy and the velocity resolution control framework can be framed in terms of (separate) task-space force fields. The system (3.7) can be captured and, at the same time, more easily generalized by the block diagram in Fig.3.2 where: the task-space force λ is now explicitly separated into $\lambda_{dyn} + \lambda_0$. In turn, λ_{dyn} can now be generalized, by the block $\Pi(x_d, x)$, to implement different types of task-space motion planners, as detailed in Tab. 3.1.

Velocity resolution control in the form of (3.8) is an open-loop control policy. Given a desired task-space trajectory $x_d(t)$, one can always derive the desired task-space velocity ($\dot{x} = \dot{x}_d$) and determine via (3.8) the joint-space velocities $\dot{q}$ to be commanded at each joint, see the controller $\lambda_{dyn} = B\dot{x}_d$ in Tab. 3.1-1. In practical applications, open-loop schemes can easily result into instability and/or unpredictable robot behaviour in presence of errors in the robot Jacobian and/or mechanical perturbations arising from the environment. Therefore, in common practice [95, 96], the task-space motion planner is usually augmented with a feedback control term $B\dot{x}_d + K(x_d - x)$ (see Tab. 3.1-2), to correct for deviations from the desired end-effector trajectory $x_d(t)$.

Figure 3.2: Posture and Motion planning via Task-space Separation Principle. For a redundant manipulator with joint-space damping W and subjected to joint-space torques $\nabla_q h$, derived from a potential field $h(q)$ (due for example to gravitational and/or elastic effects), a static, task-space, posture-dependent force field λ_0 is used for *postural control*. In particular, λ_0 blocks any effect of the joint torques $\nabla_q h$ in the task-space while leaving the manipulator free in the null-space, i.e. allowing to reach task-constrained minima of the potential $h(q)$. To perform motor tasks, an additional task-space force field λ_{dyn} is superimposed which can implement different motion planning schemes $\Pi(x_d, x)$, as shown in Tab.3.1.

Furthermore, when the task-space motion planner is as given in Tab.3.1-4, i.e. $\lambda_{dyn} = K(x_d - x)$ and λ_0 as in eq.(3.14), our framework in Fig.3.2 can be seen as a novel extension of the original PMP and will be named throughout this work as λ_0 -PMP (see Fig.3.3). It is worth noting that the original PMP models [19, 21]

Table 3.1: Possible implementations of the control schema in Fig.3.2

No.	$\lambda_{dyn} = \Pi(x_d, x)$	λ_0	Notes
(1)	$B\dot{x}_d$	eq. (3.14)	Open-loop velocity resolution control[31] as in eq.(3.8)
(2)	$B\dot{x}_d + K(x_d - x)$	eq. (3.14)	Closed-loop velocity resolution control [95, 96]
(3)	$K(x_d - x)$	$\mathbf{0}$	PMP [19, 21]
(4)	$K(x_d - x)$	eq. (3.14)	λ_0 -PMP (extension of PMP proposed in this thesis)

do not include postural control terms such as λ_0 and, without such term, the presence of a potential $h(q)$ would interfere with the task itself (see section 3.3.5 for more details).

Figure 3.3: An example of λ_0 -PMP for planning movement and postures in a redundant arm. (a) Mechanical analogy. (b) Block schema. The λ_0 -PMP is a particular instance of the more general framework shown in Fig.3.2 with $\Pi(x_d, x) = K(x_d - x)$ and $\nabla_q h = K^J(q - q_0)$. The λ_0 force compensates for the task-space components of the elastic torque τ_{el} that is therefore left free to act only in the manipulator null-space. Thanks to the λ_0 force field, the extended PMP does not only capture Donders' law but also overcome the posture/movement problem (see section 3.3.5 for more details) typical of the original PMP models (PMP1 and PMP2 in the figure)[19, 21].

3.3 Application to Wrist Pointing Tasks

Any activity involving hand manipulation requires a correct wrist coordination. If shoulder and elbow motions serve primarily for reaching objects in space, wrist movements allow to flexibly orient the hand in space and with respect to

Figure 3.4: Bones of the (right) upper limb and wrist rotations. Anatomically the wrist corresponds to the eight carpal bones providing rotations of flexion-extension (FE) and radio-ulnar-deviation (RUD). However, functionally the wrist also includes pronation-supination (PS) of the forearm hence providing a 3 DOF coupling between the hand and upper arm.

the arm. Anatomically the wrist corresponds to the eight carpal bones that connect the metacarpal bones of the palm with the forearm bones (see Fig.3.4). The relative motions between these bones make the wrist a complex biomechanical joint [97], though it is usually modelled as a two DOF universal (or Cardan) joint [30]: the radial-ulnar-deviation(RUD) allow the palm to rotate toward the radius or the ulna bones, while the flexion-extension joint let the palm rotate toward the body or away from it. The RUD axis is usually considered the most distal although subject-specific differences have been observed [98]. Even if anatomically confined in the forearm, the prono-supination (PS) rotation, achieved through the rotation of the radius about the ulna, is functionally attributed to the wrist (see Fig.3.4). Compatibly with joint limits, the combination of these three DOF let the hand assume any orientation in space.

3.3.1 Wrist kinematics during pointing tasks

The axes of rotation of the wrist are not perfectly orthogonal, nor they originate from the same point however, in what follows, this discrepancies will be considered negligible [99, 98]. Hence, kinematically, the wrist is modelled as a spherical joint with three orthogonal and intersecting axes of rotations. As shown in Fig.3.5 pointing with the wrist involves three different kinematic spaces [62]: the joint space (3D), the endpoint space (3D) and the task space (2D).

Figure 3.5: (a) Kinematic spaces and mappings for the human wrist during pointing tasks. The joint space is the set of wrist (FE and RUD) and forearm (PS) joint angles. The end point space is the set of hand orientations also known as the rotation group $SO(3)$. The task space is a planar surface (usually a computer monitor) containing desired pointing targets (in the picture are represented as circles on the monitor). The dashed gray lines on the monitor are a representation of possible task-space paths.

The joint-space comprises angular rotations (or postures) of wrist flexion-extension and radial-ulnar-deviation and of forearm pronation-supination. These 3D space can equivalently be represented via the Lie group of rigid body rotations $SO(3)$, i.e the set of rotation matrices R describing the orientation of a moving frame $\{e_1; e_2; e_3\}$ attached to the hand with respect to a fixed frame $\{e_x; e_y; e_z\}$. Equivalently, a 3×3 rotation matrix R can also be represented via a 3D rotation vector $r = \phi u$ expressing a rotation by an amount ϕ around the axis u ($|u| = 1$). A rotation matrix can be converted into a rotation vector via the matrix logarithm [100, 62]:

$$\mathbf{r} = \log_{\vee}(R) = \frac{\phi}{2 \sin \phi} \begin{bmatrix} R_{3,2} - R_{2,3} \\ R_{1,3} - R_{3,1} \\ R_{2,1} - R_{1,2} \end{bmatrix} \quad (3.16)$$

Vice versa, a rotation vector can be transformed into a rotation matrix via matrix exponential (Rodrigues' formula) [100, 62]:

$$R = \exp(\hat{\mathbf{r}}) = I + \sin |\mathbf{r}| \frac{\hat{\mathbf{r}}}{|\mathbf{r}|} + (1 - \cos |\mathbf{r}|) \frac{\hat{\mathbf{r}}^2}{|\mathbf{r}|^2}, \quad (3.17)$$

where $\hat{\mathbf{r}}$ is the skew-symmetric matrix representation of the rotation vector $\mathbf{r}$:

$$\hat{\mathbf{r}} = \begin{bmatrix} 0 & -r_z & r_y \\ r_z & 0 & -r_x \\ -r_y & r_x & 0 \end{bmatrix}. \quad (3.18)$$

For any wrist posture $\mathbf{q} := [q^{PS} \ q^{FE} \ q^{RUD}]^T$ in joint-space, the orientation R of a moving frame attached to wrist with respect to a fixed frame is computed as the ordered product of three rotations:

$$R(\mathbf{q}) = \exp(-\hat{\mathbf{e}}_x q^{PS}) \exp(\hat{\mathbf{e}}_z q^{FE}) \exp(\hat{\mathbf{e}}_y q^{RUD}) \quad (3.19)$$

and the corresponding rotation vector can be computed with eq. (3.16).

As described in section 4.2, experimental pointing tasks usually involve motion sensors that measure the 3D orientation of the wrist (in terms of rotation matrices) [62] from which individual joint rotations can be calculated as:

$$\mathbf{q}(R) = \begin{bmatrix} \text{atan2}(R_{1,3}, R_{1,1}) \\ \arcsin(-R_{1,2}) \\ \text{atan2}(-R_{3,2}, R_{2,2}) \end{bmatrix} \quad (3.20)$$

where atan2 is the four-quadrant inverse tangent. Although in general the solution to eq. (3.20) is not unique, the biomechanical range of motions of the wrist (see [62]) yields a unique joint angle configuration for any reachable orientation.

Forward kinematics

Let us consider a virtual hand-held laser (such as the sensorised handle in Fig.4.1) aligned with the axes $\mathbf{e}_1$ of the moving frame. The pointing task involves targets presented on a vertical x_1x_2 planar screen at unit distance from the wrist along $\mathbf{e}_x$ and with the y -axis of the screen directed as $-\mathbf{e}_y$. Then, for every pointing direction $\mathbf{n} = R \mathbf{e}_x$ ($|\mathbf{n}| = 1$) the laser will hit the screen at coordinates:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = FK(\mathbf{q}) := \begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix} R(\mathbf{q}) \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \quad (3.21)$$

where $R(\mathbf{q})$ is defined in eq.3.19 for simulated pointing tasks. This equation defines the forward kinematics for wrist pointing tasks (see Fig.3.5) with the task Jacobian defined as eq. (3.2).

3.3.2 Donders'law for the wrist

Pointing with the wrist is a redundant task because only two DOF (x_1 and x_2) are required to point a specific target, while, for each pointed location, the brain has to control the three DOF of the wrist (PS, FE, RUD). The additional DOF of the wrist implies that every target can be pointed with infinite wrist orientations. Despite this degree of redundancy, when pointing with the wrist (at comfortable speed) humans show a specific relationship between target directions and wrist orientation. In particular, for any desired pointing direction the wrist assumes a (statistically) unique orientation. In other words, the set of all wrist orientations measured during a trial, can be well approximated with a quadratic surface, also called Donders'law:

$$\begin{aligned} r_x &= \mathcal{D}(r_y, r_z) \\ &= C_1 + C_2 r_y + C_3 r_z + C_4 r_y^2 + 2C_5 r_y r_z + C_6 r_z^2 \end{aligned} \quad (3.22)$$

where r_x, r_y, r_z are the components of the rotation vector representing a particular wrist orientation.

Hence, despite the joint space of the human wrist is 3D the brain constraints rotation vectors to lie on a 2D surface (Donders'surface). This implies that the three DOF are not controlled independently but instead they are *coupled* in a specific *postural synergy* (Donders'surface). Such kinematic synergy has been shown to be subject specific, i.e. each subject presents a specific combination of Donders' coefficients in (3.22) [46]. The non-linear part of the quadratic Donders is captured by the coefficients C_4, C_5, C_6 : C_5 affects the amount and direction of twisting in the Donders'surface, while C_4 and C_6 determine the amount of curvature at the edge of the surface. The linear part captured by C_1, C_2 and C_3 define a plane in the 3D space of the rotation vectors, with C_2 and C_3 regulating its orientation and C_1 , as an offset, translates the synergy along the x axis. As an example, Fig. 3.6 shows a center-out trial performed by a representative subject. Fig. 3.6 (a) shows the task-space strategy employed by the subject, while Fig. 3.6 (b) shows the corresponding wrist orientations (rotation vectors) that can be well approximated by the quadratic Donders'surface. The goodness-of-

Figure 3.6: An experimental trial performed by a representative subject. Task-space paths (a) and Donders' surface fitting of rotation vectors (b). Adapted from [62].

fit is commonly evaluated with the variance-accounted-for (VAF) that indicates how much the experimental rotation vecotrs deviate from the quadratic surface [62]. The higher the VAF, the closer the rotation vectors to the quadratic Donders' surface.

3.3.3 Simulated wrist pointing tasks

This section presents simulations relative to five computational models that are special cases of the general framework proposed in section 3.2.2: 1) the open-loop velocity resolution control (OLVRC); 2) a viscous PMP model (V-PMP) that has only intrinsic viscosity W but has not intrinsic elasticity (i.e. $\nabla_q h(\mathbf{q}) = 0$) [19, 101], 3) a visco-elastic PMP model (VE-PMP) that has both intrinsic viscosity W and intrinsic elasticity (i.e. $\nabla_q h(\mathbf{q}) \neq 0$) [21] 4) the novel PMP extension proposed in this thesis, the λ_0 -PMP: a visco-elastic PMP that includes the λ_0 task-space force (see Fig.3.3); 5) a *minimum task-space effort* model where the λ_{dyn} is optimized by solving an optimal control problem parametrized with B-splines. This last model and simulations demonstrate that our framework is very general and can accommodate also the optimal control framework for the generation of optimal task-space trajectories that do not interfere with postural constraints.

The computational models were implemented in Matlab/Simulink R2012 and the differential equations were integrated with the ODE45 solver and with $dt = 0.01s$. Two different pointing tasks were investigated: the *center-out* task consists of a central target (C) plus eight peripheral targets arranged over a circle (with a radius of 15°) and oriented along the cardinal directions East(E), North-East(NE), North(N), North-West(NW), West(W), South-West(SW), South(S) and South-East(SE). The task consists of a sequence of 8 outbound movements (from

the central target to one peripheral target) alternated with inbound movements (from a peripheral target to the central target). The PMP models (V-PMP, VE-PMP and λ_0 -PMP) are compared on the *triangles* task to verify if the models are capable of generating repeatable trajectories. The triangles pointing task consists in pointing to the following sequence of targets: (C),(E), (NE),(C), (NE), (N), (C) that defines two task-space triangles (closed-loop paths). For both tasks, we set the target time (time before switching to next target) to $T = 1s$.

The goodness-of-fit between rotation vectors predicted by the models and Donders' surface fitting is evaluated with the variance-accounted-for index (VAF) [62]:

$$VAF = \left(1 - \frac{\text{var}(r_{x_i}^D - r_{x_i}^S)}{\text{var}(r_{x_i}^S)}\right) 100\% \quad (3.23)$$

where, for every simulated rotation vector $\mathbf{r}_i^S = [r_{x_i}^S \ r_{y_i}^S \ r_{z_i}^S]^T$, the corresponding rotation vector lying on the Donders' surface is calculated as $r_{x_i}^D = \mathcal{D}(r_{y_i}^S, r_{z_i}^S)$ (i.e with eq. 3.22). Hence the higher the VAF, the closer the simulated rotation vectors are to Donders' surface.

The models hereafter implemented share the same set of joint-space parameters (see Fig. 3.2): the damping W and the gradient $\nabla_q h$. It has been shown that in humans, wrist and forearm dynamics are primarily shaped by the the passive stiffness of the wrist [102, 103]. Therefore, in what follows, the potential h is assumed to be an elastic potential of the form:

$$h(\mathbf{q}) = \frac{1}{2}(\mathbf{q} - \mathbf{q}_0)^T K^J (\mathbf{q} - \mathbf{q}_0) \quad (3.24)$$

where $\mathbf{q}_0 = [q_0^{PS} \ q_0^{FE} \ q_0^{RUD}]^T$ is the *resting posture* (or *comfortable posture* [62, 63], i.e. the posture that wrist would assume if the gradient of the intrinsic potential was the only torque acting on the system) is set to:

$$\mathbf{q}_0 = [10 \ 5 \ -5]^T [deg]. \quad (3.25)$$

and K^J is a 3×3 symmetric matrix which penalizes postures away from the *comfortable* equilibrium $\mathbf{q}_0$ that for all simulations

To investigate the effect of the intrinsic damping W and the intrinsic elasticity K^J four different conditions are simulated:

- isotropic damping and low stiffness:

$$W(\mathbf{q}) = 0.02 \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \frac{Ns}{rad}, \quad K^J = \alpha I_3 \frac{N}{rad}, \quad \alpha = .008 \quad (3.26)$$

- isotropic damping and high stiffness:

$$W(\mathbf{q}) = 0.02 \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \frac{Ns}{rad}, K^J = \alpha I_3 \frac{N}{rad}, \alpha = .032 \quad (3.27)$$

- anisotropic damping and low stiffness:

$$W(\mathbf{q}) = 0.02 \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & .1 \end{bmatrix} \frac{Ns}{rad}, K^J = \alpha I_3 \frac{N}{rad}, \alpha = .008 \quad (3.28)$$

- anisotropic damping and high stiffness:

$$W(\mathbf{q}) = 0.02 \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & .1 \end{bmatrix} \frac{Ns}{rad}, K^J = \alpha I_3 \frac{N}{rad}, \alpha = .032 \quad (3.29)$$

note that the different levels of stiffness are simulated by just rescaling the eigenvalues of the stiffness K^J with the parameters α .

3.3.4 Pointing with the velocity resolution control: null-space hysteresis

Because in these simulations we do not consider motor noise or external perturbations, we focus on the open-loop velocity resolution control (OLVRC) rather than its closed-loop implementation. In addition to W and $\nabla_{\mathbf{q}}h$, OLVRC needs a desired task-space velocity $\mathbf{x}_{des}$ (see tab. (3.1)) that, for each target, was computed with a minimum-jerk profile [23] with duration equal to the target time ($T = 1s$).

The OLVRC task-space paths during the center-out task, for all four conditions are reported in Fig. 3.7 and, as expected, paths always follow straight lines regardless of the specific setting for W and K^J . This is not surprising as the OLVRC has a task-space policy $\lambda_{dyn} = B\dot{\mathbf{x}}_{des}$ and hence the joint damping W is always compensated in task-space via the B matrix.

The relative contribution between intrinsic damping and stiffness does affect joint-space paths as shown in Fig. 3.8. With the same intrinsic damping, for low level of stiffness there is what we will call *null-space hysteresis*, i.e. outbound and inbound movements follow different joint-space paths, despite they follow same task-space paths. This is especially visible in some directions. With reference to eq.(3.8), the joint-space velocity has two components: a component due to the task-space constraint (first term in (3.8)) and a null-space component that can be

Figure 3.7: Task-space paths. (a) isotropic W and low stiffness; (b) isotropic W and high stiffness; (c) anisotropic W and low stiffness; (d) anisotropic W high stiffness.

rewritten as:

$$\dot{q}_{null} = (I_n - J_W^\# J) W^{-1} \nabla_q h = N_W(q) W^{-1} \alpha K^J (q - q_0) \quad (3.30)$$

in other words the null-space velocity (or null-space dynamic) depends on the (configuration-dependent) null-space projector $N_W(q)$, and on the eigenvalues of the matrix $D = W^{-1} \alpha K^J$ [104]. So, in general, the task-space component and null-space component of the joint velocity follow different dynamics. With the setting used in these simulations, the component due to the task-space velocity extinguishes after $1s$, while the null-space will follow a slower or faster dynamic depending on the direction of motion (due to $N_W(q)$) and on the relative contribution between intrinsic damping and stiffness (see Fig.3.8). Hence,

if the null-space dynamic is slower than the task-space dynamic, the holonomic constraint imposed by $h(\mathbf{q})$ cannot be exactly followed as there is not enough time to completely minimize $h(\mathbf{q})$ in the null-space. In summary, the slower the null-space dynamic (with respect to the task-space dynamic) the larger the null-space hysteresis between outbound and inbound.

Figure 3.8: Joint-space paths. For low values of joint stiffness outbound and inbound motions follow different paths. This is because the null-space dynamic is slower than the task-space one and hence $h(\mathbf{q})$ cannot be completely optimized in the null-space. See main text for a detailed discussion.

Rotation vectors resulting from the four simulations are shown in Fig. 3.9 to-

gether with the Donders' surface fitting. The regressed Donders' surfaces are very similar (see coefficients in tab. 3.2) and this confirm that by just rescaling the stiffness K^J , the holonomic constraint imposed by $h(\mathbf{q})$ does not change. However, because for low stiffness values outbound rotation vectors differ from inbound rotation vectors, the goodness-of-fit is lower in this condition (see VAF in tab.3.2), especially for the anisotropic condition. Note that the target that is mostly pointed is the central target because it is the starting and ending position of outbound and inbound movements respectively. In addition, for the central target only, null-space motions correspond to PS motions. Because the PS damping in the anisotropic condition is double the PS damping in the isotropic condition (see eq. 3.26 and eq. 3.28), in the anisotropic condition null-space dynamics are the slowest leading to larger deviations from the Donders' constraint.

To further demonstrate that the null-space hysteresis is due to the relative speed between null-space and task-space motions, Fig. 3.10 shows joint space paths and rotation vectors in the anisotropic and low stiffness condition (i.e. the condition with the slowest null-space dynamic) where the task-space minimum-jerk trajectory has been planned with a target time $T = 10s$, simulating a very slow task-space dynamic. In this case, the null-space dynamic is (relatively) fast enough to 'fully' optimize, at each stage of the motion, the postural component $h(\mathbf{q})$ and null-space hysteresis disappears.

3.3.5 PMP vs λ_0 -PMP: repeatability and posture/movement problem

This section presents results relative to different forms of the PMP: the viscous PMP (V-PMP) that was the first one to be proposed in the literature [19] and that lacks of the intrinsic potential $h(\mathbf{q})$, the visco-elastic PMP (VE-PMP) that has both joint space damping W and intrinsic elasticity $h(\mathbf{q})$ [21] and the λ_0 -PMP, a novel extension that we propose in this work and that uses the λ_0 as additional task-space force.

For all models we set W as in the isotropic condition described previously while for the VE-PMP and the λ_0 -PMP we use the low stiffness condition described previously. All PMP models generate task-space motions by means of an extrinsic spring K that generate an elastic λ_{dyn} (see tab. 3.1) proportional to the error between the desired target $\mathbf{x}_d$ and the current task-space position $\mathbf{x}$:

$$\lambda_{dyn} = K(\mathbf{x}_d - \mathbf{x}) \quad (3.31)$$

For all three PMP implementations the extrinsic spring K was set to:

$$K = 0.1I_2 \frac{N}{m} \sim \left(J(\mathbf{q}_0)(K^J)^{-1}J^T(\mathbf{q}_0) \right)^{-1} \quad (3.32)$$

Figure 3.9: Rotation vectors and Donders' surfaces.

i.e. similar to the intrinsic stiffness reflected in task-space around the most comfortable posture $\mathbf{q}_0$. Note that in the V-PMP we use this value of K despite the joint elasticity is 0 as this model lacks of $h(\mathbf{q})$. The three models were tested with the Triangle task and with a target time $T = 1s$. All models were initialized (at $t = 0$) in $\mathbf{q}(0) = \mathbf{0}$, i.e. an initial posture different from the rest posture $\mathbf{q}_0$ (see

Figure 3.10: Joint space paths (a) and rotation vectors with Donders' fitting (b) for the anisotropic and low stiffness condition simulated by planning very slow ($T = 10s$) task-space motions. Null-space hysteresis disappear when task-space dynamics are relatively slow compared to null-space dynamics. See text for more details.

(3.25)) but pointing to the initial desired target (C).

Task-space and joint-space paths resulting from the three simulations are shown in Fig. 3.11.

Because the V-PMP has no intrinsic elastic potential it successfully perform the pointing task with straight line paths (Fig.3.11a). However, this model presents open joint-space trajectories, i.e. trajectories that are not repeatable and therefore incompatible with any kind of Donders-like constraint. This result is additionally shown in Fig. 3.12a where the PS rotation clearly accumulates after returning to the central target and reaching a final value of about 5° . PS rotation does not accumulate for the VE-PMP (see Fig. 3.12b) thanks to the intrinsic elasticity that keeps PS rotation close to the most comfortable PS rotation (10° , see eq.(3.25)). Joint-space paths are closed (Fig. 3.11d) and compatible with repeatable trajectories. However, the VE-PMP cannot reach the desired targets (Fig. 3.11c) as the intrinsic elasticity K^J reflected in task-space now counter-act the task-space elastic force due to the extrinsic spring K . Therefore in this model, postural control (due to the intrinsic potential) and motions (due to the λ_{dyn}) are not compatible (posture/movement problem), with the former interfering with the latter. The

3.3. APPLICATION TO WRIST POINTING TASKS

Figure 3.11: Task-space paths (a)-(c)-(e) and joint-space paths (b)-(d)-(f).

λ_0 -PMP instead, combines the pros of both models. Due to the λ_0 , the intrinsic elasticity K^J is not reflected in the task-space and therefore postural control is now compatible with the movement policy dictated by λ_{dyn} (see Fig. 3.11e-3.11f). This important result is further highlighted during the first second of simulation as shown in Fig. 3.12. Because at $t = 0$, $q(0)$ satisfies the task (pointing to the

central target), the V-PMP does not produce any joint motion (Fig. 3.12a). The VE-PMP instead, moves all three joints during the first second reaching a configuration that is in between the most comfortable q_0 and the one that would satisfy the task (see Fig. 3.12b-3.11c). Differently, the λ_0 -PMP only reconfigure the PS joint (null-space motions when pointing to the central target) during the first second leading to the unique optimal posture that optimizes $h(q)$ while satisfying the desired task of pointing to the central target. The λ_0 force that compensates for the intrinsic elasticity is shown in Fig. 3.13.

(a) V-PMP

(b) VE-PMP

(c) λ_0 -PMP

Figure 3.12: (a), (c) and (e) Task-space paths. (b), (d) and (f) Joint space paths.

Next section shows additional simulations of the λ_0 -PMP when performing the center-out task in the same conditions investigated for the velocity resolution control.

Figure 3.13: λ_0 force components applied by the λ_0 -PMP to compensate for the intrinsic elasticity reflected in task-space.

3.3.6 Task-space optimal control and holonomic constraints

In the previous sections we have proposed a general framework unifying several control schemes proposed either in robotics or in neuroscience. In this section we show that the proposed framework, and in particular the Task-space Separation Principle can be applied to optimal control problem as well. The work by Admiraal et al. [3] has made clear that *optimal (control) does not imply Donders' law*. However, in the next sections it is shown that the separation of postural and motion planning by means of separate λ_0 and λ_{dyn} , respectively, can be used to formulate optimal control problems to generate optimal motions that, depending on the intrinsic impedance (W and K^J) do or do not violate postural constraints such as Donders' law. This computational model shares some similarities with the hierarchical control scheme proposed in [59] whereby two separate optimal controller (one extrinsic and one intrinsic) are used to address motor redundancy.

The optimal λ_{dyn} model

One advantage of using the Task-space Separation Principle is that task-space forces are split, in task-space, into static forces (λ_0) for postural control and dynamic forces for movement control (λ_{dyn}). The postural control action λ_0 takes care of the redundancy by optimizing $h(q)$ in the null-space of the manipulator and therefore a *lower dimensional* optimal control problem can be formulated to plan optimal task-space motions minimizing some cost criteria related to the specific task to be performed. In this work we only focus on the minimization of *task-space effort*, although other choices, including the combination of multiple

cost functions [105] are possible.

Through the Task-space Separation Principle we can formulate the following (task-space) optimal control problem to plan optimal task space force λ_{dyn} that minimizes the total task-space effort:

$$\underset{\lambda_{dyn}}{\operatorname{argmin}} \left\{ \int_{t_0}^{t_f} \lambda_{dyn}^T \lambda_{dyn} dt \right\} \quad (3.33)$$

subject to:

- the task-space dynamic:

$$\dot{x} = J\dot{q} = JW^{-1} \left(J^T (\lambda_{dyn} + \lambda_0) - \nabla_q h \right) \quad (3.34)$$

where $\dot{q}$ has been expressed as in (3.15);

- the boundary conditions:

$$x(0) = x_0, \quad x(t_f) = x_f, \quad \dot{x}(0) = \dot{x}(t_f) = 0 \quad (3.35)$$

The advantage of this formulation, in presence of kinematic redundancy, is that the optimal control problem is solved on a lower dimensional space (the task-space) rather than on the full configuration space of the manipulator.

We parametrized the above problem with B-splines polynomials as proposed in [106, 107]. In particular, task-space velocities were parametrized with 4th order B-Splines and task-space forces with 2th order B-splines. Spline parameters were optimized by using sequential quadratic programming (*fmincon* Matlab function).

Results

In this section we compare the λ_0 -PMP with the optimal control approach presented in the previous section and that for brevity we will indicate as Opt. λ_{dyn} . As for the velocity resolution control, both models solve the center-out task in the four damping and stiffness conditions reported previously and with the same parameter settings. For the λ_0 -PMP the task-space spring was set as in eq.3.32. The final time (t_f) for the Opt. λ_{dyn} model was set equal to the target time $T = 1s$.

The task-space paths predicted by the two models, in the low stiffness condition, are shown in Fig. 3.14. The high stiffness condition present similar results and therefore it is not reported. When the damping matrix W is anisotropic, the λ_0 -PMP generates curved task trajectories with different paths for outbound and inbound movements (*task-space hysteresis*). This is because the λ_0 -PMP uses only an elastic λ_{dyn} (see tab. 3.1(3)) and therefore, differently from the OLVRC,

does not compensate for the task-space damping B with the result that the two task-space velocity components, $\dot{x}_1$ and $\dot{x}_2$, have different magnitudes along the trajectory (see eq.(3.36)). The Opt. λ_{dyn} instead, optimizes the task space force λ_{dyn} according to the task-space dynamic and therefore produces straight-line paths independently of the damping matrix W .

Figure 3.14: Task-space paths simulated with the isotropic (a)-(b) and the anisotropic (c)-(d) joint damping W .

The analysis in joint space reveals once again, for both models, that a null-space dynamic slower than the task-space dynamic, due to the eigenvalues of $D = W^{-1}K^J$, results into outbound and inbound movements that do not follow the same paths (Fig.3.15a-3.15b), despite task-space paths are the same for both inbound and outbound motions (Fig.3.14a-3.14b). As seen for the OLVRC, the null-space dynamic, also for these models follows eq.(3.30), and therefore depends on the relative magnitude between the intrinsic damping and elasticity. For the Opt. λ_{dyn} model the task-space speed depends on the terminal time t_f used in the cost function, the lower t_f , the faster the task-space trajectories. For the λ_0 -PMP, the task-space dynamic can be written as:

$$\dot{x} = B^{-1}(q)K(x_d - x) \quad (3.36)$$

and therefore will depend on the eigenvalues of the matrix $B^{-1}K$, where the matrix B is function of the intrinsic damping. A similar analysis can be conducted for the anisotropic damping conditions shown in Fig. 3.16.

Fig. 3.17 compares the joint trajectories for both models. When pointing to the central target, the λ_0 -PMP is capable of reaching optimal postures ($q_{ps} = 10$, $q_{fe} = 0$, $q_{rud} = 0$ [deg]) in either the low and high stiffness condition. In the low stiffness condition Opt. λ_{dyn} fails in capturing the initial and terminal postures predicted by the λ_0 -PMP. The average absolute error between the terminal postures predicted via the λ_0 -PMP with those predicted via Opt. λ_{dyn} (see Fig.3.18d) demonstrate that a faster null-space dynamic (high stiffness condition) leads to much lower postural errors between the two models.

The rotation vectors and Donders's surfaces predicted by the two models in the high stiffness condition are shown in Fig. 3.19 while, the regressed Donders' coefficients together with the VAF are reported in tab.3.2. The shape of the Donders' surface only depends on $h(q)$, however, if the null-space optimization follow a slower dynamic compared to task-space motion, rotation vectors cannot be fully constrained on the Donders' surface resulting in a lower VAF. Furthermore, notice that the task-space hysteresis typical of the λ_0 -PMP (Fig. 3.14c) also appears in joint space (Fig. 3.19c), however, differently from the null-space hysteresis, it is directed tangentially to the Donders' constraints (Fig. 3.19c).

Fig.3.20 shows the joint-space velocity profiles predicted by two models in the isotropic and high stiffness condition. While the Opt. λ_{dyn} produces bell-shaped velocities, i.e. smooth trajectories, the λ_0 -PMP velocities follow a dynamic typical of a first-order visco-elastic system.

Table 3.2: Regressed Donders' surface coefficients for different models and conditions. Notice that in the presence of null-space hysteresis (low stiffness condition with $\alpha = 0.1$), the goodness-of-fit reduces.

model	alpha	W	C1	C2	C3	C4	C5	C6	VAF
OLVRC	0.1	iso.	-0.17	-0.08	-0.07	-0.03	-0.25	0.06	91.41
OLVRC	0.1	ani.	-0.17	-0.07	-0.06	-0.03	-0.21	0.06	79.58
OLVRC	2	iso.	-0.17	-0.10	-0.08	-0.03	-0.25	0.06	99.94
OLVRC	2	ani.	-0.17	-0.10	-0.08	-0.03	-0.25	0.06	99.85
λ_0 -PMP	0.1	iso.	-0.17	-0.08	-0.07	-0.03	-0.25	0.06	90.68
λ_0 -PMP	0.1	ani.	-0.17	-0.07	-0.06	-0.02	-0.16	0.06	75.39
λ_0 -PMP	2	iso.	-0.17	-0.10	-0.08	-0.03	-0.25	0.06	99.93
λ_0 -PMP	2	ani.	-0.17	-0.09	-0.08	-0.03	-0.24	0.06	99.42
Opt. λ_{dyn}	0.1	iso.	-0.17	-0.09	-0.08	-0.03	-0.25	0.06	88.30
Opt. λ_{dyn}	0.1	ani.	-0.17	-0.08	-0.07	-0.04	-0.30	0.07	73.71
Opt. λ_{dyn}	2	iso.	-0.17	-0.10	-0.08	-0.03	-0.25	0.06	99.95
Opt. λ_{dyn}	2	ani.	-0.17	-0.10	-0.08	-0.03	-0.25	0.06	99.83

Figure 3.15: Joint space paths simulated with the isotropic joint damping W and low intrinsic stiffness (a)-(b) and high intrinsic stiffness (c)-(d).

3.4 Conclusion

This chapter addresses, from a kinematic perspective, the coordination of posture and movement in presence of redundancy. Humans are well known to solve kinematic redundancy by stereotypically selecting one specific posture to accomplish redundant tasks, a motor synergy known as Donders' law. A salient feature of human motor control is that postural control seems to subserve some static optimality purposes without interfering with the dynamics of movement generation, at least for movements performed at comfortable speed.

Pursuing a principled and bioinspired approach, this chapter blends a minimum principle framework [31], used in robotics to solve redundancy, with the

Figure 3.16: Joint space paths simulated with the anisotropic joint damping W and low intrinsic stiffness (a)-(b) and high intrinsic stiffness (c)-(d).

Separation Principle, derived from neuroscientific evidence [18]. This allows for separation of postural strategies from generation of motion.

Following [31], the velocity-resolution control has been framed as a constrained optimization problem, typically solved via the Lagrange multiplier (LM) method. However, while most of the literature treats LM as dummy variables to quickly get rid of in calculations, this chapter emphasizes that LM can be interpreted as task-space force fields.

As a first contribution, the Separation Principle is applied at the task-space level by splitting LM λ into a static and a dynamic component, λ_0 and λ_{dyn} respectively. This approach has several advantages.

3.4. CONCLUSION

Figure 3.17: Joint space trajectories during the first two outbound and inbound movements. Dark colors are relative to the Opt. λ_{dyn} model and lighter colors are relative to the λ_0 -PMP.

First, as an element of the task-space, λ_0 has the sufficient and necessary degrees-of-freedom to cancel any effect of the joint potential in the task-space itself. In other words, the presence of λ_0 allows the manipulator to achieve ‘comfortable’ positions (i.e. minimizing a postural cost) without influencing the task, i.e. to move within its null-space towards a minimum of elastic potential (the presence of joint damping W allows dissipation of energy and ensures stability). This is the key to capture postural models, as a unique joint-space configuration is associated to any given (reachable) task-space configuration.

Second, the proposed approach allows for the framing of kinematic problems in terms of force fields. One immediate advantage is that, once a kinematic problem is viewed as a force-control policy, it can be simply *superimposed* with other force-control policies, without necessarily freezing the system within an imposed Donders’ strategy. This is very important aspect because Donders’ law is known to be a ‘soft-constraint’, which can be adapted to cope with different contexts [45, 47] or violated by voluntary control [3]. Another aspect is that it is well known that the human brain can learn both dynamic and static force fields [74, 61]. The proposed approach suggests that postural models can be viewed as static force fields and could, in principle, be learned and processed by the same structure used to learn and compensate for gravity, in any posture.

Figure 3.18: Absolute total error between terminal postures simulated via the λ_0 -PMP and those simulated via the Opt. λ_{dyn} .

Third, the task-space separation of the LM also allows the formulation of a general framework that can accommodate several human motor control theories. In particular, as highlighted in Tab.3.1, several human motor control and robotic models can be accommodated in the proposed framework by using different task-space policy Π for the generation of dynamic force fields. More specifically, the velocity resolution control, the Passive Motion Paradigm and its novel extension (the λ_0 -PMP;), the minimum-task-space effort model (optimal control-based model), have been tested with simulated redundant wrist pointing tasks. The results confirm that: i) the proposed approach predicts *soft* Donders' constraints that can be violated, for example, whenever task-space dynamics are faster than (passive) null-space dynamics (due to the combined effect of intrinsic potentials and damping); ii) the proposed computational framework capture postural constraints independently of the specific task-space movement policy.

Relation to existing approaches

Since the 70s, a variety of techniques to control multiple and redundant degrees of freedom (DOF) in robots have been proposed. Although apparently different, English and Maciejewski [31] showed how most of the methods proposed in the

Figure 3.19: Rotation vectors and Donders's surface fitting in the high stiffness condition.

past are in fact specializations of a general approach first introduced by Liegeois [108]. More recently, Peters and colleagues [109] highlighted how a unifying view can be found behind these approaches, based on *Gauss's principle of least constraint*. Despite its generality, only recently [110, 111] Gauss's principle has been brought up to the attention of roboticists, who typically relied on d'Alembert's principle of virtual works to solve constrained problems in mechanics. However, Gauss's principle of least constraint is a genuine *minimum principle* [112], useful to analyze scenarios involving very general constraints in terms of constrained optimization problems, typically solved via Lagrangian multipliers.

Gauss's principle of least constraint requires the *inertia matrix* of a mechanical

Figure 3.20: Joint-space velocity profiles.

system to be defined. The inertia matrix, symmetric and positive-definite, acts as a *metric* for the system [113] defining its *geodesics* and unforced motions. This is also the key to redundancy resolution. In fact, if we push/pull an ideal manipulator through its end-effector, this will generate a *unique* motion, shaped by the inertias of its links, despite any possible redundancy. This is for example at the core of the approach proposed by Khatib and colleagues [111]. However, this approach alone would not lead to repeatable trajectories and instantaneous minimization via quadratic programming of biomechanical or robotic efforts [64, 114] is still necessary to ensure repeatability, leading to formulations similar to (3.3).

It should be noted that an ideal mechanical system consisting of joint inertias and elastic potential would not be stable, rather it would oscillated indefinitely if some form of damping is not accounted for [115], increasing thus the number of parameters. In this thesis we are interested in kinematic planning and, in some instances, inertial parameters might not even be available or necessary (e.g. planning reaching motion with obstacles avoidance). The instantaneous effort to be minimized here (eq. (3.3)) is the analogous of a viscoelastic power (3.3), first proposed by [31], which requires ‘joint damping’ W and postural cost $h(\mathbf{q})$. The damping matrix W , symmetric and positive-definite, plays the role of a metric for the system while the postural cost (3.24) has been commonly deployed to solve redundancy in both industrial and biomedical robotic applications, e.g. in recent years see [66, 116, 117].

All approaches presented so far, including ours, lead to a form of *instantaneous* minimization, formally similar to (3.3). Such an *instantaneous minimization* is different from the *global minimization* deployed, for example, in transport models [2] which however do not comply (in their original form) with Donders’ Law.

Our main contribution is to use constrained minimization of an instantaneous cost, solved with Lagrange multipliers, and apply Separation Principle to the Lagrange multipliers themselves, which can be seen as task-space forces. This is novel, to our best knowledge, and is referred to as ‘Task-space Separation

3.4. CONCLUSION

Principle'. One immediate advantage is the possibility to reformulate postural control paradigms as a force-controlled strategy which can be superimposed with other task-space strategies, as shown in Tab.3.1. In fact, this allows for global optimization to be reconsidered and applied *only* to the task-space, so expanding the list in Tab.3.1. This also leads to a form of hierarchical control similar to the framework proposed by Todorov et al. [59] to reduce the burden of computing optimal solutions for high-dimensional systems. Central to their framework is the introduction of a low-level controller that does not interfere with the desired task-space dynamics, generated and optimized via a high-level controller. Following a hierarchical control approach as in [59] we will also be able to blend transport models and optimal control in our framework. This will be part of future works, although a hint is given in section 3.3.6 with the simulations relative to the *minimum-task space effort* model.

CHAPTER 3. TASK-SPACE SEPARATION PRINCIPLE: A FORCE FIELD APPROACH
TO POSTURE AND MOVEMENT PLANNING FOR REDUNDANT MANIPULATORS

Part I

Posture

Chapter 4

Capturing Human-like Postural Kinematic Synergies via Non-linear Inverse Optimization

4.1 Introduction

The previous chapter has presented a general computational framework that allows planning posture and movement independently and without interference. In particular, it was shown that the combination of an (elastic) intrinsic potential $h(\mathbf{q})$ and the λ_0 force field predicts, at equilibrium, Donders-like kinematic synergies independently of the dynamic force field policy (II) responsible for movement. However, different intrinsic potential parameters would predict different kinematic postural synergies and therefore, the goal of this chapter, is to estimate these parameters from experimental data so that the model exhibit human-like kinematic synergies.

Following the non-linear inverse optimization algorithm proposed by Liu et al. [118], this chapter proposes an efficient algorithm to estimate subject-specific intrinsic potential parameters from the average experimental motor strategies displayed by six subjects during wrist pointing tasks. The novelty of the proposed approach is that i) Donders' law, rather than raw data, is used to filter and down-sample human behaviours; ii) the λ_0 -PMP model is used to efficiently simulate model behaviour iteratively, until it converges towards the average experimental postural kinematic strategies.

Part of the work presented in this chapter was published in [63, 91]

4.2 Assessment of postural kinematic synergies (Donders' law): experimental setup and protocol

The experimental wrist pointing strategies were assessed with the same method proposed by Campolo et al. [62].

Six right-handed healthy subjects performed the *center-out* task, shown in Fig.3.6(a), consisting of a central target (C) and eight peripheral targets arranged over a circle (with a radius of 15°) and oriented along the cardinal directions East(E), North-East(NE), North(N), North-West(NW), West(W), South-West(SW), South(S) and South-East(SE). An experimental trial consisted of a sequence of 8 outbound movements (from the central target to one peripheral target) alternated with inbound movements (from a peripheral target to the central target). After an initial familiarization phase with the setup and the task, each subject performed 10 consecutive trials.

For the entire duration of the experiment, subjects were strapped to a chair so as to minimize torso, shoulder and elbow movements. To reduce discomfort and fatigue, the forearm was mechanically supported against gravity (Fig.4.1).

Subjects grasped a light-weight 3D printed handle mounting an inertial measurement unit (IMU) (Fig.4.1) that records wrist orientations (rotation matrix R) at 120 Hz. A computer monitor was used to display the center-out task to the subject. The visual feedback consisted of the desired target position (a red circle) and the location pointed by the subject (a yellow circle). The current location pointed by the subject was update according to eq.(3.21) from the actual orientation R measured by the IMU sensor.

Before starting the experiment a 'zeroing' procedure is carried out to position the wrist in its *neutral* or *primary* position [12]. All wrist orientation recorded by the IMU are expressed with respect to this primary wrist configuration where the orientation of the fixed frame of reference coincides with the orientation of the moving frame recorded by the IMU. Eq.(3.16) was used to convert wrist orientations into rotation vectors that were in turn used to regress quadratic Donders' surfaces as in eq.(3.22). As shown in Fig.4.2, although for every subject trial-by-trial rotation vectors can be well approximated by Donders' surfaces, across different trials the Donders' surface tends to 'drift' along the x direction, while the surface' shape tends to be consistent accross trials [62]. Such drift is probably related to PS rotations (when pointing to the central target ($r_z = r_y = 0$) and $r_x = -q_{ps}$) [62] and section 7.2.3 gives one possible explanation of such phenomena.

Figure 4.1: Experimental wrist pointing setup. Wrist orientations are measured with an inertial measurement unit (IMU) mounted on a light-weight 3D printed handle, hence functioning as a ‘virtual’ laser pointer. The equations for mapping measured wrist orientations R into: task-space locations (pointer position) x , rotation vectors r (used to fit Donders’ surfaces) and wrist joint configurations q are reported in section 3.3.

4.2.1 Inverse optimization to capture experimental postural kinematic synergies

It has been shown that the dynamics of wrist and forearm rotations are mostly dominated by the intrinsic stiffness [102, 103]. Therefore, in what follows, we assume that the intrinsic potential responsible for kinematic synergies is an elastic potential of the form:

$$h(q; K^J, q_0) = \frac{1}{2}(q - q_0)^T K^J (q - q_0) = h(q; \theta) \quad (4.1)$$

where $\theta = [K_{11}^J, K_{12}^J, \dots, K_{33}^J, q_0^{PS}, q_0^{FE}, q_0^{RUD}]$ is a 9-dimensional parameter vector containing six stiffness parameters (because the matrix K^J is assumed symmetric) and three resting posture q_0 . Clearly, the choice of the parameter vector in eq. (4.1) influences the particular pointing strategy predicted by the computational framework proposed in Chapter 3. In other words, different parameter vectors θ , result into different postural synergies or Donders’ surfaces. The following sections show how to estimate the parameter vector θ from the experimental wrist orientations. This class of problems is known as *inverse optimization* or *inverse optimal control* and it has recently received increasing popularity in the fields of human motor control [118, 119, 120] and humanoid robotics [121, 122]. For parametric cost functions as in eq.(4.1), Liu et al. [118] have proposed a non-

(a) subject 1

(b) subject 2

(c) subject 3

(d) subject 4

(e) subject 5

(f) subject 6

Figure 4.2: Donders' surfaces during the ten center-out trials. Across trials the surface shape shows little variability however it tends to drift along the x direction that, when pointing to the central target ($r_z = r_y = 0$), corresponds to PS rotations: $r_x = -q_{ps}$. See [62] for more details.

4.2. ASSESSMENT OF POSTURAL KINEMATIC SYNERGIES (DONDER'S LAW): EXPERIMENTAL SETUP AND PROTOCOL

linear inverse optimization (NIO) algorithm that can efficiently cope with high dimensional biochemanical models. Adapted to our specific problem, their algorithm reads as follow: given a human pointing strategy ($Q^H; X^H$) measured at N time samples $t_1, t_2, \dots, t_N$ with $Q^H = \begin{bmatrix} \mathbf{q}^H(t_1) & \mathbf{q}^H(t_2) & \dots & \mathbf{q}^H(t_N) \end{bmatrix}$ and $X^H = \begin{bmatrix} \mathbf{x}^H(t_1) & \mathbf{x}^H(t_2) & \dots & \mathbf{x}^H(t_N) \end{bmatrix}$ being, respectively, the concatenated postural and task configurations where $\mathbf{q}^H(t_i)$ is a subject-specific wrist configuration pointing at the location $\mathbf{x}^H(t_i) = FK(\mathbf{q}^H(t_i))$.

Given a simulated pointing strategy $Q^M = \begin{bmatrix} \mathbf{q}^M(t_1) & \mathbf{q}^M(t_2) & \dots & \mathbf{q}^M(t_N) \end{bmatrix}$ such that for each time sample t_i , $\mathbf{x}^H(t_i) = \mathbf{x}^M(t_i) = FK(\mathbf{q}^M(t_i))$ (i.e. the task-space locations pointed by the human are used as a task-space constraints for the model), the optimal parameter vector $\boldsymbol{\theta}$ can be estimated by minimizing the following error function:

$$e(\boldsymbol{\theta}) := \sum_{i=1}^N \left(h(\mathbf{q}^H(t_i), \boldsymbol{\theta}) - h(\mathbf{q}^M(t_i), \boldsymbol{\theta}) \right) + s(\boldsymbol{\theta}) \quad (4.2)$$

where $h(\mathbf{q}^H(t_i), \boldsymbol{\theta})$ is defined in eq. (4.1) and $s(\boldsymbol{\theta})$ is an additional cost function penalizing parameters that would produce degenerate solutions or that are not consistent with the problem formulation. It is defined as:

$$s(\boldsymbol{\theta}) = (Trace(K^J) - 4)^2 + \sum_{k=1}^6 \mu_k(\theta_k) \quad \text{where} \quad \begin{cases} \mu_k(\theta_k) = (\theta_k - \theta_k^{max})^2 & \text{if } \theta_k \geq \theta_k^{max} \\ \mu_k(\theta_k) = (\theta_k - \theta_k^{min})^2 & \text{if } \theta_k \leq \theta_k^{min} \\ \mu_k(\theta_k) = 0 & \text{otherwise} \end{cases} \quad (4.3)$$

where the first term on the right hand-side enforces the trace of the stiffness matrix to be equal to $4 \frac{Nm}{rad}$ to get stiffness values that are of the same order as those measured experimentally [103] and θ_k^{min} , θ_k^{max} represents the minimum and maximum bounds, respectively, of the parameter θ_k . In this way we add a penalty whenever the rest posture $\mathbf{q}_0$ falls beyond the human wrist range of motion ([62]) and/or any of the k_{ii} becomes negative. Note that no penalty was introduced for the three off-diagonal coefficients of the stiffness matrix and therefore in (4.3) $k = 1, \dots, 6$.

The rationale behind eq. (4.2) is that since for a given parameter vector $\hat{\boldsymbol{\theta}}$ the model generates motion with minimum cost, the human motion will always have an higher cost or $\sum_i h(\mathbf{q}^H(t_i), \hat{\boldsymbol{\theta}}) > \sum_i h(\mathbf{q}^M(t_i), \hat{\boldsymbol{\theta}})$. To decrease the error between the two costs, Liu[118] suggested to locally approximate (around a given estimate $\hat{\boldsymbol{\theta}}$) the gradient of the error function with following equation:

$$\nabla_{\boldsymbol{\theta}} e(\boldsymbol{\theta}) \simeq \sum_{i=1}^N \nabla_{\boldsymbol{\theta}} h(\mathbf{q}^H(t_i), \hat{\boldsymbol{\theta}}) - \sum_{i=1}^N \nabla_{\boldsymbol{\theta}} h(\mathbf{q}^M(t_i), \hat{\boldsymbol{\theta}}) + \nabla_{\boldsymbol{\theta}} s(\hat{\boldsymbol{\theta}}) \quad (4.4)$$

In what follows the NIO algorithm [118] is adapted to estimate subject-specific

parameters of the intrinsic potential (eq. (4.1)). The main differences of the proposed approach with respect to [118] are: 1) the experimentally measured Donders'surfaces are used to down-sample and smooth the human trajectory; 2) the λ_0 -PMP model is used to generate the model pointing strategy Q^M instead of solving a constrained optimization problem with a nonlinear optimizer [118].

Filtering and down-sampling the experimental data

NIO requires a human pointing strategy (Q^H, X^H) from experimental data. With reference to Fig.4.3.(1) it is possible to notice that during the ten pointing trials the experimental recording is made of thousands of samples (N) that are also affected by the instrumentation noise. The higher the number of samples, the higher the computational burden needed to run the NIO as, for each human sample a corresponding sample must be generated by the model. Therefore, a reliable method must be implemented in order to filter first and then down-sample human raw data. Fig.4.3.(2) shows the (average) Donders'surface that best fits the rotation vectors of a representative subject during ten pointing trials. Apart from being a kinematic pointing synergy, this surface can also be thought as a filter applied to the experimental rotation vectors. Furthermore, it can be used to generalize the subject pointing strategy to pointing directions that have not been measured experimentally. Based on these considerations the following method is proposed to down-sample the human pointing strategy: given a subject-specific Donders'surface (eq. (3.22)), a small set of N_0 rotation vectors $\tilde{r}^H = \begin{bmatrix} r_1^H & r_2^H & \dots & r_{N_0}^H \end{bmatrix}$ are generated by sampling the Donders's surface at N_0 different locations as shown in Fig.4.3.(3); then, the down-sampled rotation vectors are mapped into down-sampled joint configurations, providing a set $\tilde{Q}^H = \begin{bmatrix} q_1^H & q_2^H & \dots & q_{N_0}^H \end{bmatrix}$ of joint angles. This set of joint angles is needed to compute the error function in eq. (4.2) and to update the parameter vector (eq. (4.4) and eq. (4.5)). The set of N_0 joint angles is mapped into N_0 desired task-space constraints $\tilde{X}^H = \begin{bmatrix} x_1^H & x_2^H & \dots & x_{N_0}^H \end{bmatrix}$ and are used as desired targets to generate motions with the λ_0 -PMP model (see Sec.4.2.1). In the following a set of $N_0 = 9$ points consisting of a central point plus 8 peripheral points were chosen (note that the theoretical minimum would be 6 points, in order to capture quadratic surfaces which can be described by 6 coefficients).

Estimating the parameter vector θ from down-sampled data

The NIO algorithm described in this section is shown as a flowchart in Fig.4.4. The input to the algorithm are the down-sampled human pointing strategy $(\tilde{Q}^H, \tilde{X}^H)$ and an initial guess for the parameter vector $\hat{\theta} = \theta_0$ (see section 4.3).

Step 1. The λ_0 -PMP model is simulated with joint potential $h(q, \hat{\theta})$ defined

4.2. ASSESSMENT OF POSTURAL KINEMATIC SYNERGIES (DONDERS' LAW): EXPERIMENTAL SETUP AND PROTOCOL

Figure 4.3: Filtering and down-sampling of human raw data. (1) Rotation vectors of a representative subject during ten pointing trials. (2) Rotation vectors are fitted with the quadratic Donders surface. (3) The $r_y r_z$ plane is sampled at $N_0 = 9$ points. For each of these points, $N_0 = 9$ rotation vectors are generated via the Donders' law: $r_{z_i} = \mathcal{D}(r_{y_i}, r_{z_i})$ with $i = 1, \dots, N_0 = 9$. These down-sampled rotation vectors are then mapped into joint and task-space to form a down-sampled experimental pointing strategy ($\tilde{\mathbf{Q}}^H, \tilde{\mathbf{X}}^H$).

by the current estimate of the parameter vector $\hat{\boldsymbol{\theta}}$ and with the desired pointing targets $\tilde{\mathbf{X}}^H$ coming from the human down-sampled data. For each desired pointing target, the equilibrium wrist configurations (at steady-state) generated by the λ_0 -PMP model are collected: $\tilde{\mathbf{Q}}^M = [\mathbf{q}_1^H \quad \mathbf{q}_2^H \quad \dots \quad \mathbf{q}_{N_0}^H]$.

Step 2. Given the human pointing strategy $\tilde{\mathbf{Q}}^H$, the model pointing strategy $\tilde{\mathbf{Q}}^M$ and the actual estimation of the parameter vector $\hat{\boldsymbol{\theta}}$, a gradient direction is approximated by evaluating $\nabla_{\boldsymbol{\theta}} e(\boldsymbol{\theta})$ (eq. (4.4)).

Notice that the λ_0 force field, at equilibrium, is metric-independent and therefore the result of this section are not affected by the specific W used to simulate the λ_0 -PMP model. See section 3.2.1 for more details.

Step 3. The parameter vector is updated as:

$$\hat{\theta} \leftarrow \hat{\theta} - \beta \nabla_{\theta} e(\theta) \quad (4.5)$$

where the scalar β is computed with a line search method as in [118]. The algorithm is then repeated j_{max} times, specified as input to the algorithm by the user.

Figure 4.4: The Nonlinear Inverse Optimization (NIO) algorithm used to estimate subject-specific intrinsic potential h . Note that, differently from [118], the λ_0 -PMP model was used at every iteration to optimize the parameter vector θ .

4.3 Results

For each subject, the experimental rotation vectors resulting from the ten pointing trials were fitted with the quadratic Donders' surface that in turn was used to sample nine rotation vectors from which the corresponding task-space positions $\tilde{X}^H$ and joint-space configuration $\tilde{Q}^H$ were calculated (see Fig. 4.3).

For the initial guess θ_0 , the stiffness matrix in eq. (4.1) was initialized as $K^J = 1.33I_{3 \times 3}$ ($I_{n \times n}$ being the $n \times n$ identity matrix) and the resting posture q_0 was initialized at the center of the wrist range of motion (see [62]). To speed up the computation without losing in accuracy, the λ_0 -PMP model (Step 1. of the algorithm) was simulated with the variable step size ode15s solver (Simulink 2012) with: Max Step Size= 0.1[s], Min Step Size= 0.0001[s], Initial Step Size= 0.001[s], Relative Tolerance = auto, Absolute Tolerance = auto. The task-space stiffness

4.3. RESULTS

$K = 10 \cdot I_{2 \times 2} \frac{Nm}{rad}$ and joint-space damping $W = 0.02 \cdot I_{3 \times 3} \frac{Nms}{rad}$ were set in order to have fast convergence to steady-state so as to reduce the computational burden while at the same time keeping the evolution of the system stable. Hence, each desired pointing target x_i^H was simulated for 1 (s) and the equilibrium configuration q_i^M was selected as that corresponding to the last sample of the simulation. The NIO was terminated after 700 iterations.

Fig.4.6 shows the individual stiffness ellipsoids relative to the potential fields estimated via the NIO algorithm. The stiffness ellipsoids are a graphical representation of the 3D stiffness K^J . The minor and major axes of the ellipses represent the directions of lower and higher stiffness respectively and highlight that all but subject six show an anisotropic joint-space elastic field. The resting posture q_0 estimated via the NIO defines the center of each ellipsoid. For comparison, it is also shown an isotropic elastic field (sphere) of $0.5 \frac{Nm}{rad}$. The estimated parameters for each subject are reported in Tab. 4.1-4.2 and their distribution are shown as box plot in Fig. 4.5. The diagonal stiffness coefficient, K_{fe} (or K_{22} in 4.1), was found to be on average higher than K_{ps} (or K_{11} in 4.1) and K_{rud} (or K_{33} in 4.1), and K_{ps} on average was the lowest. Although a paired ttest revealed that only K_{11} was statistically different from K_{22} . The off-diagonal stiffness coefficient were always lower than the diagonal ones. K_{pf} and K_{pr} (representing the coupling between PS and FE and PS and RUD respectively) were tightly distributed around zero, while K_{fr} had a broader distribution with a prevalence of positive values. The distribution of the most comfortable postures are shown in Fig.4.5(b). The q_0^{ps} was the most variable coefficient with preference for positive values. Differently, q_0^{rud} was mainly negative except for one subject while q_0^{fe} showed a broad tuning around the zero.

Table 4.1: Subject-specific intrinsic stiffness (K^J) parameters estimated via NIO from the average postural kinematic strategy. Stiffness subscript correspond to: 1 = PS, 2 = FE, 3 = RUD, so that the stiffness K_{12} corresponds to the stiffness along the PS-FE direction.

$[\frac{Nm}{rad}]$	K_{11}^J	K_{12}^J	K_{13}^J	K_{22}^J	K_{23}^J	K_{33}^J
subj 1	1.22	0.07	0.08	1.68	0.03	1.09
subj 2	1.20	0.04	-0.12	1.47	0.26	1.33
subj 3	1.25	-0.08	0.00	1.63	0.11	1.12
subj 4	1.21	0.10	-0.15	1.24	0.29	1.54
subj 5	1.26	0.00	-0.08	1.21	0.16	1.52
subj 6	1.30	-0.01	-0.04	1.42	-0.05	1.27

After the estimation was completed, the six subject-specific intrinsic potentials were used to solve the center-out task with the λ_0 -PMP model. As shown in Fig.4.7 the Donders'surfaces, fitting the model-generated rotation vectors (colored surfaces), are in good agreement with both the curvatures and the offsets

Table 4.2: Subject-specific resting postures (q_0) estimated via NIO from the average postural kinematic strategy.

[rad]	subj 1	subj 2	subj 3	subj 4	subj 5	subj 6
q_0^{PS}	0.26	0.51	0.06	0.36	0.35	0.23
q_0^{FE}	-0.08	0.11	0.04	0.25	0.12	0.03
q_0^{RUD}	0.13	-0.11	-0.19	-0.09	-0.07	-0.04

(a)

(b)

Figure 4.5: Distribution of the parameter vector θ (K^J and q_0) estimated via NIO.

of the average experimental Donders' surfaces (black grids) found for each subject. The colors of the simulated Donders' surface represent, in each point, the *torsional error* between experimental and simulated rotation vectors:

$$error_i = ||(r_i^H|| - ||r_i^M|| \quad (4.6)$$

where r_i^H is a rotation vector belonging to the experimental Donders and r_i^M is the rotation vector predicted by the λ_0 -PMP when pointing in the direction $||r_i^H||$. As shown by the color bars in Fig. 4.7 this error is always below 1.5° and therefore within the range of thickness (deviations of the experimental rotations vector from the Donders surface) measured experimentally [62]. Fig. 4.7 also highlight that the highest torsional errors are around the zero of the Don-

4.3. RESULTS

Figure 4.6: Estimated postural costs. The minor and major axes of each ellipsoid represent the directions of smaller and higher stiffness respectively. Each ellipsoid is centred on the most comfortable posture q_0 . The inner spheres are used as reference and represent an isotropic elastic field of $0.5 \frac{Nm}{rad}$. Crosses mark the origin of each plane.

ders' surface where the torsional error corresponds to the error between the PS angle assumed by the human and the PS angle predicted by the model when both point to the central target (C).

Figure 4.7: asadas

Figure 4.8: Experimental Donders' synergies (black grid) compared with those predicted via the postural model with optimized discomfort parameters (colored surface). Colours represent the torsional error (in degree) between experimental synergy and model predicted synergy. In zero, i.e. when both model and subjects are pointing to central target the torsional error corresponds to the error between the PS angle assumed by the human and the PS angle predicted by the model.

4.4 Conclusion

In this chapter an efficient non-linear inverse optimization method has been proposed to estimate subject-specific potential function parameters from experimen-

tal pointing tasks. Although the NIO was readapted from literature [118], the novel contributions have been: i) the use of the Donders' surface to down-sample and filter the experimental pointing strategies and ii) instead of solving a constrained optimization problem with a nonlinear optimizer, the λ_0 -PMP model was used to simulate, iteratively, the model pointing strategy. This approach lead to a very efficient NIO algorithm that could be executed for several iterations (700 times in this thesis) and that resulted in a very accurate prediction of the experimental kinematic synergies. Furthermore, it has been shown that, at least for the human wrist, the computational framework proposed in chapter 3 and in particular the λ_0 -PMP, can be used to simulate and predict human-like kinematic synergies.

Chapter 5

Assessment of Postural Muscular Synergies

5.1 Introduction

The control of posture and movement in humans appear to be challenging because of the many degrees-of-freedom (DOF) of our musculoskeletal system. Previous chapters have focused on the problem of kinematic redundancy and it was shown that several experimental scenarios have highlighted the presence of postural kinematic synergies (such as Donders' law), i.e. specific patterns of joints covariation that 'eliminate' kinematic redundancy by reducing the effective number of available kinematic DOF. The human body however, also possesses hundreds of muscles and therefore task requirements in general are not sufficient to uniquely specify how each muscle should be controlled. According to the *muscle synergies hypothesis* the brain might simplify the complex mapping between desired tasks and muscle activations through the use of *muscle synergies*: task-specific group of muscles (or modules) that are coherently activated in space or time. Therefore, according to this hypothesis the brain does not control each muscle individually, but forms muscle groups that are controlled independently.

The muscle synergy hypothesis is usually tested by applying factorization algorithms (such as principal component analysis, or non-negative matrix factorization,..., see [123] for a complete overview) to electromyographic (EMG) signals recorded from multiple muscles during human motor control experiments. For example, D'Avella and colleagues have shown that during reaching movements in vertical planes the muscle activity of 19 shoulder and arm muscles can be captured by four to five time-varying muscle synergies. In a subsequent study they have shown that during reaching movements in different directions and with different speeds muscle activity is generated by modulating only two types

of synergies: *phasic synergies*, modulated for different task direction and speed, were found to be primarily responsible for movement i.e. to accelerate and decelerate the arm; *tonic synergies*, modulated for different task directions and not substantially with speed, were found to be responsible for antigravity and postural control. These results were found to be compatible with the hypothesis of a Separation Principle for the brain.

While the muscle synergy hypothesis assume that muscles are always coordinated synergistically (i.e. in groups), Kutch and colleagues [32] have proposed the compelling hypothesis of a *flexible* muscle activation strategy according to which the brain flexibly chooses between a *prime mover strategy* where a single muscle is activated to generate force in a given direction and a *synergistic strategy* where multiple muscles are recruited to produce force in a given direction. To validate this alternative hypothesis, they developed a method that uses the variability of isometric force production (target-directed variance) as an indicator of the underlying muscle strategy. The main assumption underlying their method is that muscles generate forces that are corrupted by signal-dependent noise. Therefore, if a single muscle is activated to generate force in a target direction, then the muscle mechanical action and the target direction must be aligned. In addition, the force variability will be directed along the target direction, reflecting the signal-dependent noise of the activated muscle. Differently, if multiple muscles are activated to produce a desired force in a given direction, the force variability does not align with the target direction but is broadly distributed reflecting the signal-dependent noise arising from different muscles. The advantage of this method is that, in isometric conditions, the presence or not of muscle synergies can be quantified without recording muscle activity. In addition, for those muscles that are activated as a prime mover, the method let identify their biomechanical actions.

In this chapter we describe a preliminary and ongoing work that we have been performing to find out if during isometric pointing tasks wrist muscles are controlled synergistically or flexibly. The ultimate goal of this type of study is to elucidate if wrist postural kinematic synergies (such as Donders' law) can be somehow related to wrist muscle activation patterns.

5.2 Materials and methods

Four right-handed healthy subjects (two females, two males), participated in the experiment. Their mean age was 25.2 ± 3.7 and they had no history of neurological disorders.

Subjects controlled a 2D cursor displayed on a computer screen by applying isometric wrist torques on a 3D printed handle whose extremity was rigidly

connected to a 6-axis load-cell (ATI mini-40, ATI Industrial Automation inc.) as shown in Fig.5.1. The relationship between wrist joint torques and the load-cell force/torques is shown in Fig.5.2. The wrist frame of reference was assumed to be located at the capitate bone [124] and subjects were strapped to the handle so that the force sensor frame of reference had (approximately) zero vertical displacement with respect to it ($dz = 0$ in Fig.5.2). We also assumed that the FE axes and the RUD axes were aligned ($dRUD = 0$ in Fig.5.2). The distance dx between the origin of the force sensor frame of reference and the origin of the wrist frame of reference was measured for each subject. Wrist torques were acquired with a 1000 Hz sampling frequency.

The horizontal displacement of the cursor was proportional to the FE joint torque, the vertical displacement was proportional to RUD joint torque and the cursor orientation was controlled by the PS torque. The cursor was made of a red circle and a yellow bar indicating the cursor orientation (see Fig.5.3(a)). Subjects were instructed to keep the yellow bar vertical, so as to avoid the generation of PS torques, to avoid cross-talking of the muscular activity. Starting from a relaxed condition, in which the cursor appeared at the centre of the computer screen, a trial consisted in moving the cursor at a desired target torque and keeping this target torque for 5 seconds (holding period). This holding period was used to extract target-directed torque variability as described below. The experiment consisted of 48 trials (or targets), i.e 2 force levels and 24 directions, as shown in Fig.5.3(a).

Prior to the beginning of the experiment, subjects performed maximum-voluntary-contraction by applying separately RUD torques and FE torques. The two level of torques for the experiment were set as the 25% and 50% of the maximum recorded wrist torques. The main wrist muscles involved in the generation of flexion-extension and radial-ulnar-deviation torques [125, 126] are shown in Fig. 5.4.

Quantification of target-directed torque variability

Following Kutch et al. [32] torque fluctuations across different target directions were quantified using the *target-directed variance* η that measures the degree to which the torque covariance in each trial is aligned with the desired target torque for that trial. Because different muscles have different pulling directions (as shown in Fig.5.3(b) and Fig.5.4), the target-directed variance indicates the contribution of muscles to the desired direction as prime mover or as a synergy. To calculate the parameter η along each direction, the time series of the FE torques and of the RUD torques relative to the 5s holding period were combined into a torque matrix T . Then, the target torque T_{target} was calculated as the average torque vector $\bar{T}$ and, the vector $\hat{T}_{target}$ corresponded to the target torque normalized to have unit length. Subsequently, wrist torques were band-pass filtered

Figure 5.1: The experimental setup used for the isometric experiment.

Figure 5.2: Relationship between force/torques measured at the load-cell and wrist torques. The wrist frame of reference was assumed to be located at the capitate bone and subjects were strapped to the handle so that the force sensor frame of reference had (approximately) zero vertical displacement with respect to it ($dz = 0$). We also assumed that the FE axes and the RUD axes originated at the same point ($dRUD = 0$). The distance dx between the load-cell frame of reference and the wrist frame of reference was measured for each subject.

5.2. MATERIALS AND METHODS

Figure 5.3: (a) The isometric task consisted in the production of 48 different forces: 2 levels of forces in 24 directions. (b) Muscle-pulling directions for the wrist measured in [126] in a similar wrist configuration used in this experiment.

Figure 5.4: The main wrist muscles controlling wrist flexion-extension and radial-ulnar-deviation. Adapted from Wikipedia.

(zero-phase-lag fourth order Butterworth) in the range 8 – 40 Hz so as to filter-out any voluntary contribution to the torque variability. These filtered torques T_{filt} were used to compute the target-directed variance as:

$$\eta = \frac{\hat{T}_{target}^T \text{cov}(T_{filt}) \hat{T}_{target}}{\text{Trace}(\text{cov}(T_{filt}))} \quad (5.1)$$

where $\text{cov}(T_{filt})$ is the covariance matrix of the filtered torques. When η is equal to 1, all torque variability is directed along the target direction (prime mover strategy), differently, low values of η indicates that most of the variability is not directed along the target direction and therefore multiple muscles are activated to generate that specific target torque (synergistic strategy).

EMG processing and extraction of muscle synergies

During the experiment, muscle activity was recorded from the five main wrist muscles (ECRL, ECRB, FCU, FCR, ECU), whose mechanical-pulling directions in the FE-RUD plane have been quantified in [126] and are shown in Fig.5.3(b). The surface electromyographic activity (EMG) was measured with a BIOPAC MP150 data acquisition and analysis system connected to a National Instruments NI-USB 6463 device for data synchronization and acquisition. The sampling frequency for the EMG activity was 1500 Hz. The raw EMG signals were high-pass filtered at 35 Hz, rectified and low-pass filtered at 40 Hz [33]. The filtered EMG signals were synchronized with the force data and, for each trial, only the EMG signals relative to the 5s holding period were considered. The EMG activity was normalized with respect to the maximum value of the overall activity and then further normalized to have unit variance so that the activity in all muscles was equally weighted [33].

For each target, we calculate the integral of each filtered EMG signal and these integrals were assembled into an EMG matrix M of $5\text{muscles} \times 48\text{targets}$.

Non-linear matrix factorization was employed to extract N muscle synergies, i.e. the M matrix was approximated as [33, 123]:

$$M \sim WH \quad (5.2)$$

where W is a $5 \times N$ matrix, whose columns W_i indicate the contribution of each muscle to synergy i and H is an $N \times 48$ matrix whose rows H_i , called the *activation coefficients*, indicate how much the synergy i contribute to each target. We used the non-linear matrix factorization algorithm proposed in [127] that returns scaled activation coefficients so that each synergy vector W_i has unit length.

For each subject, non-linear matrix factorization was executed iteratively from $N = 1$ to $N = 5$ and the number of synergy N_{syn} was set according to the method

described in [33].

Comparison between torque variability and muscle synergy

To relate muscle synergies with force variability we employ the method proposed in [33]. For each target, we compute the sum of all activation coefficients of the all synergies, defining what we will call the *target-directed synergies activation*. Then, the Pearson's coefficient r_p is used to correlate the target-direct variance η with the target-directed synergies activation.

5.3 Results

The torque trajectories during the 48 hold periods are shown for a representative subject in Fig. 5.5. In red color are shown the covariance ellipses together with their principle axis. For all subjects we found that the activity of the five muscles could be captured by $N_{syn} = 4$ muscle synergies that are shown in Fig.5.6. Fig.5.7 shows the target directed variance η (black markers) and the target-directed synergies activation (red markers) for each subject. The averages between the two torque level conditions are well fit with an ellipse that helps visualizing the directions of maximal target-directed variance and maximal target-directed synergies activation. By comparing this figures with Fig.5.3(b), we notice that for subject 1,2 and 3, the maximum target-directed variance (black ellipse) is in the direction Radial-Flexion and Ulnar-Extension, and hence FCR and ECU could be the prime mover muscles for these subjects. Differently, for subject 4 the target-directed variance is mostly directed along the Radial-Extension and Ulnar-Flexion direction, suggesting that ECRL and/or ECRB and FCU could be the prime mover muscles for this subject. For subject 1,2,3 the target-directed synergies activation has its maximum values in the Flexion-Extension direction and therefore these subjects co-activate FCR and FCU to produce flexion torque and ECRL/ECRB and ECU to produce extension torque. For subject 4 the target-directed synergies activation is tilted in the direction Radial-Flexion/Ulnar-Extension and therefore his synergistic strategy differ from the previous subjects. In each plot in Fig.5.7 are reported the the correlation coefficients r_p between the target-directed variance and the target-directed synergies activation together with their p value. As expected, for all subjects the correlation is negative, i.e. to higher target-directed variance corresponds lower target-directed synergies activation, however the correlation is significant only for subject 2 ($p < 0.05$). Fig.5.8 shows the average target-directed variance and target-directed synergies activation of all subjects with a significant negative correlation between the two indicators.

Figure 5.5: Torque trajectories during the 48 holding periods.

Figure 5.6: Subject-specific muscles synergies.

5.4 Conclusion

In this preliminary experiment we tested two different methods to understand whether wrist muscles are coordinated in a synergistic or prime mover fashion. Using the target-directed variance method, we hoped to find subject-specific muscle pulling directions. However, this preliminary results reveal, in accordance with previous findings [34], that wrist muscles, during isometric torque generation, are mainly controlled in a synergistic fashion and therefore it is not

5.4. CONCLUSION

Figure 5.7: Target-directed variance (black) and target-directed synergies activation (red). Different markers are relative to different torque levels. The average between the two torque level is fitted with an ellipse.

possible to isolate the five muscle pulling directions. Only for one subject there was a significant correlation between synergistic control and target-direct variance, however such correlation was significant when the target-directed variance and the target-directed synergies activation were averaged among all subjects. In conclusion, this preliminary study suggests that the prime-mover strategy is only directed along one specific directions and that wrist muscles are mostly under synergistic control. We are not able to tell whether subject four is an outlier or the control of wrist muscle is subject-specific. Future studies should include a larger number of subjects in order to better clarify this last point. Furthermore, future works should be devoted to understand if any relationship can be identified between muscular control and postural kinematic synergies, i.e. if there is any relationship between target-directed synergy activations (Fig. 5.7) and stiffness ellipsoids responsible for kinematic synergies (Fig. 4.6).

Figure 5.8: Target directed variance (black-colors) and target-directed synergies activations (red colors) averaged for all subjects and for both level conditions.

Part II

Movement

Chapter 6

Effects of Mechanical Impedance (joint stiffness and damping) on Wrist Movement

6.1 Introduction

Simulations in chapter 3 have highlighted that the mechanical impedance of the wrist is the main component that shapes both posture and movement planning in the general computational framework proposed in section 3.2. More specifically, while an intrinsic elastic potential allows capturing Donders-like postural strategies, the joint damping W affects both joint-space and task-space dynamics, especially for the λ_0 -PMP model, where an anisotropic joint-space damping leads to curved and hysteretic (outbound and inbound movements follow different paths) task-space paths.

Task-space hysteresis has been shown to be a peculiar aspect of wrist rotations [35]. In particular, when performing the center-out task with the two DOF of the wrist (FE and RUD), task-space paths show the following three features: 1) outbound and inbound paths curve to opposite sides; 2) movements in the same direction but to opposite targets curve to the same side; 3) fast movements are more curved than comfortably paced movements [35]. In a subsequent experimental study [102], the same authors characterized the impedance of 2 DOF wrist joint and they showed that inertial and damping torques are one order of magnitude lower than torques due to joint stiffness. They then presented a computational model for the wrist and concluded that, the characteristic pattern of curvatures are due to anisotropic joint elasticity [128].

The main hypothesis pursued in this chapter is that, a Donders-fitted model λ_0 -PMP, i.e. fitted to only capture postural strategies, is also able to predict human-like movement. To this end, we extend the experimental results in [35]

to redundant wrist pointing tasks (i.e. involving FE, RUD and PS rotations). We found that all subjects perform curved task-space paths and, in some directions, these paths also feature hysteresis. We then performed λ_0 -PMP simulations to capture subject-specific movement features. While intrinsic potential parameters (K^J, q_0) were estimated on a subject-specific basis to capture the experimental postural strategies (chapter 4), rather than using damping parameters to fit *a posteriori* the experimental motions, in line with experimental evidence [129, 130, 131, 103], we make the *a priori* hypothesis that joint-space damping is proportional to joint-space stiffness. This remarkably allows a postural-fitted model to also capture dynamic performance such as curvature and hysteresis of task-space trajectories, confirming and extending previous findings in literature. We therefore posit that, in the hypothesis of a Task-space Separation Principle for the brain and, of a λ_0 compensation of the intrinsic elasticity, (anisotropic) joint-space damping rather than (anisotropic) joint-space stiffness is responsible for the characteristic pattern of wrist curvatures.

6.2 Methods

6.2.1 Donders-fitted λ_0 -PMP

With reference to Fig. 3.3, for the λ_0 -PMP, once the Jacobian matrix J is defined (given the geometry of the manipulator and of the task), the parameters which need to be determined are the *intrinsic stiffness matrix* K^J and the rest posture q_0 ; the *intrinsic damping matrix* W (or, equivalently, the admittance W^{-1}); and the *extrinsic stiffness matrix* K .

Subject-specific intrinsic stiffness K^J and rest posture q_0 from experimental data

The intrinsic potential parameters (K^J, q_0) (Tab. 4.1- 4.2) derived with the non-linear inverse optimization approach presented in chapter 4 are used to implement a subject-specific *Donders-fitted λ_0 -PMP model*. In chapter 4 it was shown that the model can accurately capture subject-specific postural strategies and in the next sections we shift our focus on task-space dynamics, which are primarily shaped by the damping matrix W .

Damping W and intrinsic time constant

While the intrinsic stiffness matrix is derived directly from a fitting process of experimental data, for the intrinsic damping matrix W , rather than trying to use the coefficients of the matrix W as ‘extra degrees of freedom’ to better fit experimental data, we assume that *damping is proportional to stiffness*, in line with

experimental evidence [129, 130, 131, 103]. In other words, we hypothesize that the same biomechanical factors which determine the ‘shape’ (in terms of eigenvectors and eigenvalues) of K^J will determine a similar ‘shape’ for W . For this reason we set the damping to be proportional to the intrinsic stiffness

$$W = \tau_0 K^J \quad (6.1)$$

where τ_0 is a scalar (positive) value with the units of time, and can be therefore thought of as an *intrinsic time constant*. The reason is that, for a simple scalar, linear spring-damper system, the ratio between damping and stiffness determines exactly the time constant of the system.

Extrinsic stiffness K and task-space dynamics

The extrinsic stiffness K is responsible for the task-space dynamics together with the task-space damping $B(\mathbf{q})$, as highlighted in (6.3). However, $B(\mathbf{q})$ is determined once J and W are given, as in eq. (3.11). In this work, we are considering very simple center-out tasks, as described below. As there is no *a priori* preferential direction in the task-space, we shall consider an *isotropic* extrinsic stiffness. Furthermore, to plan biologically-plausible bell-shaped velocities [22], following [115], we shall consider time-varying (isotropic) stiffness:

$$K(t) = k \cdot \left(1 - e^{-\frac{t}{\tau}} - \frac{t}{\tau} e^{-\frac{t}{\tau}} \right) \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (6.2)$$

that, as shown in Fig. 6.1, has the property of increasing its stiffness value from zero to k with an *extrinsic time constant* τ (notice that when pointing to a new target the time t is reset to zero in simulation).

Remark: With reference to the diagram in Fig. 3.3, the task-space damping $B(\mathbf{q})$ in (3.11) transforms task-space velocities $\dot{\mathbf{x}}$ into task-space forces which balance out the effect of the extrinsic spring K , leading to the following task-space dynamic equation:

$$B(\mathbf{q})\dot{\mathbf{x}} = K(\mathbf{x}_d - \mathbf{x}) \quad (6.3)$$

Although the task-space damping is posture-dependent and more equations are needed to fully solve the dynamics, some remarkable properties can already be noted: *i*) the task-damping $B(\mathbf{q})$ in (3.11) directly depends on the intrinsic damping W which, therefore, directly affects task-space dynamics (6.3); *ii*) the intrinsic stiffness K^J does not appear in (6.3) (being intrinsic elastic torques compensated in the task-space by the λ_0 force field) and therefore does *not* directly affect the task dynamics, however, it does it *indirectly* through postures adjustments in the null-space which affect the Jacobian and therefore $B(\mathbf{q})$.

Figure 6.1: Time-varying task-space stiffness as in eq.(6.2). The time constant τ_0 regulates the speed with which the maximum value k (set to 10 in this figure) is reached.

6.3 Comparative analysis of task-dynamics: experimental pointing tasks vs Donders-fitted λ_0 -PMP model predictions

In this section, we will compare the *average* experimental trajectories during wrist pointing tasks with those predicted via a *Donders-fitted* λ_0 -PMP model, i.e. a λ_0 -PMP model for which the *only postural parameters are fitted to capture the Donders law for a specific subject*. The main hypothesis is that a Donders-fitted λ_0 -PMP model, i.e. fitted to only capture postural strategies, is also able to display path human-like movement feature as experimentally found by Charles and Hogan [35]. A major difference with their experimental paradigm is that their subjects only used FE and RUD movements, as PS movements were restrained, so it was not a redundant task. In our case, subjects are free to rotate the forearm about the PS axis, adding a degree of redundancy.

For the task-planner, we shall assume as extrinsic $K(t)$ as in (6.2) for all subjects, in particular *isotropic* and therefore *not directly responsible for path curvatures*. Both the intrinsic (τ_0) and extrinsic (τ) time constants are set on a subject-specific and movement specific basis as $\tau = \tau_0 = \frac{T}{5}$, where T is the average time that the subject requires to perform a specific movement. Similar to (6.1), we used the

time-constant τ_0 to tune the scalar stiffness k in (6.2) as:

$$k = b_{max}/\tau_0 \quad (6.4)$$

where b_{max} is the maximum eigenvalue of the matrix $B(\mathbf{q}_0)$ and $\mathbf{q}_0$ is the initial wrist configuration prior to the starting of the movement. Therefore, k was set on a subject-specific (because of $B(\mathbf{q})$) and movement-specific basis (because τ depends on the average time T that the subject needs to perform the movement).

6.3.1 Experimental protocol and data analysis

The experimental data used in this chapter comes from the same experimental protocol and subjects described in section 4.2, i.e. six right-handed healthy subjects performing center-out wrist pointing tasks at self-paced speed (see section 4.2 for more details). Differently from chapter 4 where the focus is on postural control, here we are mainly interested in task-space dynamics, in particular the fact that trajectories during pointing tasks with the wrist appear more curved than in similar tasks performed with the arm [35]. To this end, we follow the same data analysis method proposed in [35]. Specifically, the recorded kinematic data is first filtered with smoothing splines [132, 35] to ease numerical differentiation in estimating task-space velocity profiles. The starting and ending times of a movement are identified from the task-space tangential velocity profiles: the start of movement is set to occur at the time of the first data sample *before* the velocity peak with a value below 20% peak velocity. Similarly, the end of a movement is set to occur at the time of the first data sample *after* the velocity peak with a value below 20% the peak velocity. Movements featuring a path length and/or a duration beyond two interquartile from the (subject-specific) median were excluded from the analysis. To compute the average trajectory of a movement, the data was normalized with respect to the movement time and then linearly interpolated at 20 equally temporally spaced samples.

Path curvature and hysteresis

To assess path curvature in task-space, we follow the method proposed in [35] to test whether task-space paths are on average curved and if so, whether outbound and inbound movements had different direction of curvatures. More specifically, since each movement occurs between two targets, we consider the straight-line connecting the two targets and directed from the initial target to the final one. This direction is used to determine whether the actual movement is on the left or on the right of the straight line, as depicted in Fig. 6.2. In particular, we shall consider the whole area enclosed between the actual movement and the straight line and split this area into ‘right area (A_R), i.e. the enclosed area to the right of the

straight line and 'left area (A_L) as the enclosed area to the left of the straight line. Both left and right areas are defined non-negative and are normalized with respect to the square of the nominal target-to-target distance ($(\frac{\pi}{12})^2 [m^2]$). For each movement, either inbound or outbound, we compute the following measures:

- total area $A_{sum} := A_R + A_L$ (non-negative by definition), indicating deviations of the actual movement from the straight-line.
- net area $A_{net} := A_R - A_L$, indicating tendency of a path to deviate more on the right ($A_{net} > 0$) or to the left ($A_{net} < 0$).

Finally, since an outbound movement is always followed by an inbound movement, we also consider the *path hysteresis* defined as $A_{hyst} := A_{net}^{OUT} + A_{net}^{IN}$, i.e. the area enclosed in between outbound and inbound paths.

To assess the statistical significance of each measure, we use a *t-test* (with $\alpha = 0.05$) to test the following hypotheses: 1) paths are curved ($A_{sum} \neq 0$); 2) outbound paths have a preferred curvature direction ($A_{net}^{OUT} \neq 0$); 3) inbound paths have a preferred curvature direction ($A_{net}^{IN} \neq 0$); and 4) an outbound-inbound sequence presents hysteresis ($A_{net}^{OUT} \neq -A_{net}^{IN}$).

Figure 6.2: Movement curvature is assessed by calculating the area enclosed to the left (A_L) and to the right (A_R) of the straight-line connecting the starting and ending of a movement. The total area $A_{sum} = A_L + A_R$ indicates whether movements are curved and the net area A_{net} whether there is a tendency to veer more on the right ($A_{net} > 0$) or to the left $A_{net} < 0$.

6.3.2 Results

For all subjects and for all movements we found A_{sum} to be statistically different from zero suggesting that task-space paths executed with the wrist are not straight also in presence of redundancy (this was not the case in [35], where PS was locked).

Fig. 6.3 shows the average outbound and inbound paths of the six subjects together with their standard deviations (shaded areas). Thick lines mark move-

6.3. COMPARATIVE ANALYSIS OF TASK-DYNAMICS: EXPERIMENTAL POINTING TASKS VS DONDERS-FITTED λ_0 -PMP MODEL PREDICTIONS

ments for which A_{net} was statistically different from zero (i.e. a preferred curvature direction) while stars mark segments with statistically significant hysteresis (i.e. outbound and inbound follow different paths). Superimposed with experimental trajectories, Fig. 6.3 also shows the task-space trajectories predicted via a Donders-fitted λ_0 -PMP model (dashed lines).

Fig. 6.4 compares the experimental A_{net} (average and standard deviation) with the model predicted A_{net} . This comparison indicates whether the simulated paths have the same curvature direction and magnitude as the experimental ones. A t-test ($p < 0.05$) was used for each movement to assess if the average A_{net} was statistically different from the model predicted A_{net} (stars).

With reference to Fig. 6.3a, subject 1 shows path hysteresis only for the (SW) target, while, the only statistically different A_{net} were found for inbound movements from the (W) and the (SW) target (red thick lines) that both veer to the right. With reference to Fig. 6.4a, there is no statistical difference between the model and the experimental curvatures when pointing to and from the (N) and the (W), from (NW) and to (S) targets. The model is particularly accurate in capturing the average curvature of the (N) inbound, the (S) inbound and the (W) outbound and inbound. Overall, for this subject the model can only capture the curvature of 6 out of 16 movement direction (37%).

With reference to Fig. 6.3b, subject 2 presents hysteresis for most of the targets, except for the (E), (SW) and (SE). This subject presents preferred curvature direction when pointing to and from the (W) target, with outbound and inbound both veering to the right. There is also a preference to veer to the right and to the left when performing outbound movements toward the (SW) and (S) targets, respectively. Fig. 6.4b shows that, for all movements, the model predicts curvatures that are not statistically different from the experimental ones.

Similar analysis can be conducted for the remaining subjects. Here we limit ourselves to observe that for subject 3 there were no differences in terms of curvatures in 11 out of 16 movements (about 70% of movements). For subject 4 there were no differences between model and experimental curvatures in 10 out of 16 movements (62% of movements). For subject 5 there were no differences between model and experimental curvatures in 8 out of 16 movements (50% of movements) and for subject 6 in 9 out of 16 movements (56%).

In summary, task-space curvature and hysteresis appear to be subject- and movement-specific and the model can capture most of this features for the majority of movements and subjects.

The experimental and simulated joint space trajectories are shown in Fig. 6.5 (only outbound and inbound movements from the (E) the (W) target are shown). All subjects show high variability when coordinating the PS rotation (red area), most likely because this is the joint that adds redundancy to the pointing task.

The model can accurately reproduce the average FE (magenta color) and RUD (green) trajectories for most of the subjects and movements, while for PS rotations, there are larger errors between the average experimental trajectory and the model.

At the starting and ending times of each movement, i.e. when the wrist is stationary, the model predicted postures only depends on the estimated parameters K^J and q^* . So, the larger the error between the model and the experimental posture, the less accurate is the estimate of K^J and q^* . Because we are setting W proportional to K^J , part of the errors between the model and the experimental trajectories may be due to the error between the real intrinsic subject stiffness and the one estimated from the data. In addition, the model does not take into account inertial and gravitational contributions. While the former has very little effect on wrist and forearm rotations [103], gravity torques have been found to be non-negligible [103].

Fig. 6.6 compares the experimental task-space tangential velocity profile and those predicted by the model for a representative subject. The time-varying extrinsic spring (6.2) reproduces bell-shaped velocity profiles similar to the experimental ones, although, task-space velocities predicted by the model tend to be slightly higher than the experimental ones.

6.4 Conclusion

This chapter focused on human motor strategies during redundant pointing tasks performed with wrist (and forearm) rotations. In a previous work, Charles and Hogan [35] showed that when pointing with the wrist, task-space paths are curved and in general, inbound and outbound movements follow different paths. In a successive work, they posited that such features of wrist rotations are due to an anisotropic joint stiffness matrix.

Here, based on the Task-space Separation Principle and the novel computational model proposed in chapter 3 we put forward the hypothesis that anisotropic intrinsic damping, rather than stiffness (being the intrinsic wrist elasticity compensated in task-space by the λ_0 force field), is primarily responsible for curved task-space paths. The novel aspect of our approach is that our model was fitted to capture postural strategies and, with the sole hypothesis that intrinsic damping is proportional to stiffness (eq. (6.1)), the model also exhibited curvatures and hysteresis in task-space performance remarkably similar to subject-specific average motions. More specifically, we found that i) task-space paths are curved also in presence of kinematic redundancy, extending thus the work of Charles et al. [35] where the PS axis was locked; ii) curvature and hysteresis found in experimental trajectories, on a subject-specific and target-specific basis, are a possible

consequence of postural constraints.

There are of course many approximations and assumptions in our model which, as mentioned, is not meant to predict exact trajectories but rather capturing some basic features of human-like motion. A major limitation is that the intrinsic stiffness K^J is only a very simplified attempt to approximate the real, nonlinear, time-variant mechanical stiffness typically of human arm. This in turn affects not only the predicted postural strategies (i.e. wrist configuration at the beginning and ending of a movement) but also the predicted trajectories as the relationship between damping and stiffness is certainly more complex than the simple proportionality assumed in (6.1).

A second limitation is that the λ_0 -PMP totally neglects feedback, as it is meant to address *motion planning* rather than execution. Our model is however useful at a planning stage, while feedback should be incorporated for movement execution.

As a third limitation, our model is to be considered as a *first order postural and motor planner*, in the sense that it does not take into account the inertial properties of the human or robotic arms. This is a specific choice (in some cases an inertia might not even be available, e.g. in motor imagery scenarios) and the model could be extended to include inertial properties. In fact, the role that the manipulator intrinsic inertia would have is the same that the intrinsic damping has in our model. Such an approach would lead to models along the lines proposed by Khatib [114].

In conclusion this chapter presents an extended version of the PMP that can deal with kinematic redundancy in compliance with Donders' law, can solve the posture/movement problem and predict human-like movement trajectories. Just like the PMP [101, 87, 21], the λ_0 -PMP model can find extensive use in planning human-like motions for humanoid robots and, at the same time, be able to capture *natural postures* in compliance with Donders' Law.

Figure 6.3: Task-space trajectories. Shaded areas are the standard deviation of each movement. Thick lines mark paths with A_{net} statistically different from zero (i.e. a preferred curvature direction). The stars mark movements with A_{net}^{OUT} statistically different from A_{net}^{IN} , i.e. those movement that present hysteresis.

6.4. CONCLUSION

Figure 6.4: Experimental vs Model predicted A_{net} . Error bars represent the standard deviation of the experimental A_{net} . Stars mark a model-predicted A_{net} that is statistically different ($p < 0.05$) from the average experimental A_{net} .

Figure 6.5: Joint space trajectories (PS in red, FE in magenta and RUD in green), predicted by the model (dashed lines) and measured experimentally: mean (continuous line) and standard deviations (color areas). The letters indicate the target sequence. For instance, the first movement is an outbound movement toward the target (E), the second movement is an inbound movement from target (E) to target (C) and so forth.

Figure 6.6: Task space velocity profiles of a representative subject (mean (continuous line) and standard deviation and those predicted by the λ_0 -PMP (dashed line)).

Chapter 7

Conclusion and Outlook

The dichotomy between postures and movements has driven experimental investigations, computational models as well as theories of human motor control for decades. Postural control in humans has been widely investigated during kinematically redundant tasks involving pointing and/or reaching with different body parts. From these type of experiments, Donders' law emerged as a holonomic kinematic constraint subserving postural control of eye, head and wrist joints. For the upper arm there has been contrasting evidence. The work by Soechting and colleagues [52] showed that the final arm configuration depends on the starting position and therefore Donders' law would not apply to arm coordination. However, very recently, Ewart and colleagues showed that the variability of terminal posture arising from different starting position is not statistically different from the variability of the terminal posture reached from the same starting position and therefore they suggested Donders' law also applies to unconstrained and visually guided reaching movements [48].

Perhaps, also because of Donders' law volatility (see section 2.3.2) computational models have focused more extensively on generation of motion in non-redundant tasks, rather than postural control mechanisms. In any case, rarely posture and movement were investigated at the same time. Differently from postural control, movements have been mostly studied in non redundant kinematic settings, mainly involving planar reaching movements executed with shoulder and elbow. To date, optimal feedback control is one of the most recognized theories of human motor coordination that explains both motor invariance and motor variability typical of planar reaching movements. However, as reported in the introductory chapter of this work, the current implementation of optimal control frameworks are not compatible with Donders' law. On the other hand, constrained optimization of an intrinsic potential function has been shown to account for Donders' law, yet, without solving the problem of movement planning.

The main objective of this work was to develop a general and bio-inspired

computational framework that can accommodate both motion planning and the flexibility of Donders-like postural control during redundant pointing tasks.

7.1 Major contributions

- Task-space Separation Principle & postural kinematic synergies.** In its current formulation and implementation, the Separation Principle [18] is applied at the joint-space level and it is assumed that all static torques (either due to the gravity or to elastic fields) are perfectly compensated by the brain. The Separation Principle, combined with an optimal control approach, can explain several features of human reaching movements, yet, it does not predict Donders' law being the terminal posture dependent on the starting position [18]. Differently, the novelty of the proposed approach is in applying the Separation Principle only to the task-space, deriving thus a *static* task-space force field (λ_0) which only produces a partial compensation of static joint torques due, for example, to gravitational or elastic potentials. The advantage of using force-fields in task-space rather than in joint-space, is that static joint torques are now left free to act in the null-space, driving postures towards minima of intrinsic potentials ($h(\mathbf{q})$) without interfering with task-space objectives. This captures the essence of *postural kinematic synergies, such as Donders law, which can now be seen as generated from a joint-space potential and a task-space force field.*
- Lagrange multipliers as task-space forces.** The starting point of our formulation was to frame kinematic redundancy as a constrained optimization problem, similarly to what has been done in robotics for the velocity resolution control framework. In robotics, constrained optimization problem are usually solved with the method of Lagrange multipliers (LM). While most of the literature treats LM as dummy variables, *this thesis emphasizes that LM act as task-space force fields.* In particular, in Chapter 3 we showed that, the concurrent constrained minimization of a configuration-dependent potential $h(\mathbf{q})$ and a dynamic cost defined through a positive-definite symmetric matrix $W(\mathbf{q})$, leads to the task-space superposition of a static (or configuration-dependent) LM (λ_0) and a dynamic (velocity-dependent) LM (λ_{dyn}).
- Force-field approach.** By re-framing kinematic problems via the *superposition* of separate task-space force fields for the control of posture and movement, this thesis proposes a general computational framework whereby movements can be generated by any task-space force field policy $\lambda_{dyn} = \Pi(\mathbf{x}_d, \mathbf{x})$ without interfering with postural control. Since the task-space has

in general a lower dimensionality than the joint-space, (optimal) movement policies can be efficiently encoded in the proposed framework, alleviating the *course of dimensionality* problem typical of the optimal control framework [59].

- **An efficient NIO method.** Human-like kinematic constraints have been captured with a novel and efficient non-linear inverse optimization method capable of estimating model parameters from the experimental pointing strategies.
- **Human-like movement from postural constraints.** It has been shown that a Donders-fitted computational model (the λ_0 -PMP), i.e. a model fitted only to capture postural strategies (i.e. equilibrium postures) can also predict dynamic features, such as curvature and hysteresis, typical of human wrist pointing movements.

7.2 Ongoing & Future works

Future works will be devoted to a more detailed analysis of biomechanical aspects underlying the control of wrist movements, to an extension of the framework that include also motor noise and sensory integration as well as to the modelling of biologically plausible neural implementations of the Task-space Separation Principle.

7.2.1 Is there any ‘biomechanical intelligence’ behind human null-space motions?

A common approach in robotics (and motor neuroscience) is to employ a single internal model of the manipulator that compensates, in joint-space, both non-linear dynamics due to Coriolis and centripetal torques and static torques due to gravity and intrinsic joint elasticity. Then, to solve kinematic redundancy, a *virtual* joint-space potential $h(\mathbf{q})$ is minimized in the manipulator null-space so as to avoid singularity and/or joint saturations [133, 134]. The torque $\nabla_{\mathbf{q}}h$ arising from the virtual potential can therefore be considered as an active component of robot controller. Differently, according to the Task-Space Separation Principle, $h(\mathbf{q})$ could be a *real* potential field that the brain only compensates in task-space. Hence, in this case, *null-space motions are not actively controlled but arise passively*.

Does the brain has full null-space control or are null-space motion due to passive dynamics?

Active null-space control by means of virtual potentials make sense for traditional robots that are characterized by heavy and bulky links where intrinsic

friction and elasticity are kept as small as possible. For these robots, leaving the null-space uncontrolled and subjects to passive dynamics may lead to joint saturations under the effect of gravity torques [134]. Contrary to robots, human biomechanics features light-weight bones linked together by visco-elastic components such as muscles, tendons and skin. It is therefore possible that in humans stable null-space motions may passively arise from the interplay of intrinsic elasticity and extrinsic potentials due to gravity or applied by external means [65, 135]. Again, with the assumption that the brain compensate only the task-space effect of all these configuration-dependent contributions via the force field $\lambda_0(q)$.

Very little is known about null-space control and learning in humans as most of the studies have investigated non-redundant planar reaching movements. However, several experiments have shown that the brain can cope and adapts to task-space force fields [74]. It is also known that the brain can learn separately, i.e. without interference, dynamic and static task-space force fields [135]. The work by Mistry and Schaal [134] demonstrated that when perturbing force fields are applied to each of the seven DOF of the human arm, the brain only compensates perturbing torques that interfere with the desired task, hence leaving the null-space freely to evolve under the perturbing actions. Very recently, wrist and forearm rotations measured experimentally during center-out tasks have been compared with: i) an optimal control model minimizing different criteria and ii) with a model where only FE and RUD were actively controlled while the PS rotations were due to passive and coupled dynamics [136]. It was found that this very last model could more accurately predict the observed pattern of wrist rotations. While these authors do not provide a justification on why the brain does choose FE and RUD and leave PS uncontrolled rather than choosing a different combination of the controlled/uncontrolled joints, the Task-Space Separation Principle does provide a more general and principled explanation of this result, being the null-space mostly directed along the PS axis.

With reference to Fig. 2.3, it was hypothesized that, depending on the particular task constraints, the brain employs different postural strategies by changing the parameters of a ‘velocity-box’ [45, 47]. The Task-space Separation Principle however, offers an alternative explanation: the brain may adapt the $\lambda_0(q)$ force field to the specific task constraints being the potential $h(q)$ dependent on the biomechanics and geometrical configuration (that ultimately affect both elastic and gravitational contributions) of the specific joints required to solve the task.

In conclusion, future works should be devoted to answer the following question: how much ‘biomechanical intelligence’ hides behind human null-space motions?

7.2.2 Task-space Separation Principle & Motor Cortex

Is there any Task-Space Separation Principle in our brain? If so, where? One hypothesis could be that the configuration-dependent task-space compensation $\lambda_0(q)$ is like an internal model of configuration dependent potential fields $h(q)$ and therefore could be implemented in the cerebellum [71, 137]. The control of posture and movement of the oculomotor system for example, appear to be implemented by different neural circuits of the cerebellum, the floccus and the oculomotor vermis, respectively [137]. Alternatively, the additive and reciprocal action of the λ_{dyn} as movement planner and λ_0 as postural controller could be implemented in the motor cortex. The work by Kurtzer and colleagues showed that M1 neurons are specialized into two different control processes: one for the control of postures ('tonic' neurons) and one for the control of movements ('phasic' neurons)[61]. Additivity, also seems to be an important aspect underlying cortical neurons computation [138, 139]. Kalaska and colleagues recorded motor cortex activity in monkey during the execution of reaching movements in different directions and under different load conditions. Again, they found that neural cells could be grouped into phasic and tonic groups each with different degrees of sensitivity for the applied load. In particular, tonic cells that mostly respond to maintained limb postures where also those that mostly responded to changes in load conditions (a phenomenon that resemble the calculation of the $\lambda_0(q)$), while the activity of phasic cells that mostly responded during the execution of movements was not affected by different load conditions (a phenomenon that resemble the λ_{dyn} computation). Furthermore, because the population activity was approximately the linear sum of the movement-related activity without external loads and the tonic activity caused by the external loads, authors argued that motor cortex neurons may be organized according to the Separation Principle. The works by Graziano and colleagues have shown that electrical stimulation of monkey motor cortex evokes movement of the arm to a specific postures, independently of the initial arm configuration or of the load applied to the hand [140, 141, 142]. From these findings, Capaday and colleagues have very recently argued that Donders'like constraints may be planned in the motor cortex [143, 48].

It is still debated whether the motor cortex neurons represents kinematic aspects (such as postures, movement directions, velocities) or dynamic aspects (such as force/torques) of movements [144, 145, 146, 138] and whether this computation is carried out in extrinsic (task-space) or intrinsic (joint-space) coordinates [141]. In addition, most of the previous works have not consider neural activity during kinematically redundant tasks and therefore, with the state of the art is difficult to state whether in the motor cortex is implemented a (joint-space) Separation Principle or a Task-Space Separation Principle. The hope, is that the

task-space force field framework proposed in this work, with the separation of dynamic force fields for movement planning and static force fields for postural control, may serve as a future reference to elucidate neural computations underlying cortical and sub-cortical neurons.

7.2.3 Force Fields Learning, Proprioception and Sensory Integration: Why Does Donders' surface drift?

Several machine learning techniques have been employed to learn Jacobian maps [21, 147, 148] and metric tensors [149, 150, 151]. If and how the brain learns Jacobians and metric tensors we do not know, however, in our framework they both play an important role for the trajectory generation and for the λ_0 compensation. If the brain implements the Task-Space Separation Principle, how does it compute the configuration dependent λ_0 (eq. (3.14))? One possibility is that, depending on the particular context, the brain may learn separately $\nabla_q h$, W , its task-space representation B and the Jacobian J so that the λ_0 is nothing but $BJW\nabla_q h$. Alternatively, the brain may use a single configuration-dependent mapping from joint configuration to task-space force fields, i.e. $\lambda_0(q)$. In any case, the mapping depends on the current configuration q , that, differently from the simplifying assumptions of our model, is affected by sensory-motor noise and delays. Movement planning and control requires a correct estimate of the hand configuration with respect to the desired target. To reduce uncertainty about the hand location, the brain optimally integrates both proprioceptive and visual modalities. It has been shown that, when subjects perform a sequence of point-to-point reaching movements between two targets, if the visual feedback of the hand is suddenly removed, the hand paths gradually drifts from the target positions however, the geometric features of the path (length and direction) remain unchanged [152]. Such phenomena can be explained by considering that the absence of visual feedback increases the uncertainty of this sensory modality and therefore compromises the overall estimation of the hand location [153]. It has also been hypothesized that the drift may be due to separate controllers of movements and positions each of which relying on different sensory modalities [152].

In line with these finding, we have been extending the computational framework presented in this work so as to account for sensory integration. Indeed, pointing with the wrist requires a 2D visual feedback and a 3D proprioception. We believe that this mismatch between vision and proprioception is the cause of the Donders' surface drift (see Fig.4.2) that may lead to uncertain proprioceptive informations and hence affect the λ_0 estimation.

During the past years we have also investigated task-space force field learning in virtual [77] and real haptic environments [154] with the H-Man robot

[155, 156] (Fig.7.1.(a)). Our study revealed that proprioception is indeed an important component of the learning process [77]. As shown in Fig.7.1.(c), we have been developing a novel version of the H-Man end-effector to investigate task-space force fields learning in the presence of motor redundancy. We hope that this approach will elucidate the mechanisms behind postural and movement control and, if and how the brain manages to implement any form of Task-Space Separation Principle.

7.2.4 Biomechanics and Control of Human Wrist During Contact Tasks

Wrist control is quintessential for any kind of manipulation task. Although in this thesis we have only addressed the control of free pointing movements and the control of muscles and forces in isometric conditions, during the past years we have also been addressing wrist control during contact tasks. Specifically, we are interested in both biomechanical and control aspects of human wrist during tooling tasks such as polishing and grinding. To this end, we have been developing sensorised tools to measure contact forces, motions and muscle activities involved during these tasks (see Fig.7.2). A preliminary study has been published in [157] and we are currently facing the problem of wrist impedance estimation. Our ultimate goals are: 1) understanding the control and learning of contact tasks; 2) transfer human skills into robotic end-effectors.

Figure 7.1: (a) The H-Man robot. (b) The H-Man is a 2 DOF haptic device for the rehabilitation of shoulder and elbow. (c) We have been modifying the H-Man's end-effector to add an additional (passive) DOF for wrist movements. This will let us study task-space force fields learning in kinematically redundant tasks.

Figure 7.2: Human wrist control during contact tasks. We have developed a sensorized tool to measure both contact forces and positions/orientations of the tool in space. By combining this information with muscle activities we wish to identify how humans modulate wrist impedance during these kind of tasks.

Author's Publications

1. **Tommasino, P.**, Campolo, D. - *Taskspace separation principle: a force-field approach to motion planning for redundant manipulators*. Bioinspiration & Biomimetics 12, 2 (2017), 026003.
2. **Tommasino, P.**, Campolo, D. - *Human-like pointing strategies via non-linear inverse optimization*. International Conference on Biomedical Robotics. Biorob 2016. IEEE.
3. Phan, G.H., Hansen, C., **Tommasino, P.**, Hussain, A., Campolo, D. - *Instrumentation of a hand-held power tool for capturing dynamic interaction during finishing tasks*. International Conference on Biomedical Robotics. Biorob 2016. IEEE.
4. **Tommasino, P.**, Hussain, A., Budhota, A., Hughes, C. M., Dailey, W., Campolo, D. (2015, August). *"Feel the Painting": a clinician-friendly approach to programming planar force fields for haptic devices*. International Conference on Rehabilitation Robotics (ICORR), 2015. IEEE.
5. Hussain, A., Dailey, W., Hughes, C., **Tommasino, P.**, Budhota, A., Gamage, W. G., Campolo, D. (2015). *Preliminary feasibility study of the H-Man planar robot for quantitative motor assessment*. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2015. IEEE.
6. Hughes, C.M., **Tommasino, P.**, Budhota, A., Campolo, D. *"Upper extremity proprioception in healthy aging and stroke populations, and the effects of therapist- and robot-based rehabilitation therapies on proprioceptive function."* Frontiers in Human Neuroscience 9 (2015).
7. Hussain, A., Dailey, W., Hughes C.M., **Tommasino, P.**, Budhota, A., WG Gamage, Burdet, E., Campolo, D.- *Technology intervention in neurorehabilitation A practical approach to teaching*. 6th International Conference on Robotics in Education,, RiE 2015".
8. **Tommasino Paolo**, Welihena GKC, Lorenzo Masia, Charmayne ML Hughes and Domenico Campolo - *A Novel Robot for Arm Motor Therapy with Homogeneous Mechanical Properties*. IEEE International Conference on Control, Automation, Robotics & Vision, ICARCV 2014, Singapore.
9. Phan Gia Hoang, **Paolo Tommasino**, Muhammad Azhar, Welihena G, Asif Hussain, Domenico Campolo - *Characterization of impedance rendering with a cable-driven agonist-antagonist haptic device*. IEEE International Conference on Control Automation Robotics & Vision (ICARCV), 2014, Singapore.

10. Campolo, D., **Tommasino, P.**, Welihena GKC Gamage, Klein, J., Hughes, C., Masia, L. - *H-Man: A Planar, H-shape Cabled Differential Robotic Manipulandum for Experiments on Human Motor Control*. Journal of Neuroscience Methods 235 (2014): 285-297.
11. Caligiore, D., **Tommasino P.**, Sperati, V., and Baldassarre, G., "*Modular and hierarchical brain organization to understand assimilation, accommodation and their relation to autism in reaching tasks: a developmental robotics hypothesis.*" Journal of Adaptive Behavior 22, no. 5 (2014): 304-329.
12. **Tommasino, P.**, Masia, L., Welihena GKC Gamage, Muhammad, A., Hughes C., Campolo, D., - *H-Man: Characterization of a Novel, Portable, Inexpensive Planar Robot for Arm Rehabilitation*. IEEE International Conference on Biomedical Robotics and Biomechatronics, BioRob 2014, São Paulo, Brazil.
13. **Tommasino P.**, Eng, Y.N., Gia Hoang, P., Widjaja, F., Gamage, K., Campolo, D., - "*Learning Coriolis-type force fields without robots*". 3rd IFToMM International Symposium on Robotics and Mechatronics, ISRM 2013, Singapore.
14. **Tommasino P.**, Melendez-Calderon, A., Burdet, E., Campolo, D., (2014) *Motor adaptation with passive machines: A first study on the effect of real and virtual stiffness*. Computer Methods and Programs in Biomedicine, Volume 116, Issue 2, 145 - 155.
15. **Tommasino, P.**, Caligiore, D., Mirolli, M., Baldassarre, G. "*Reinforcement learning algorithms that assimilate and accommodate skills with multiple tasks.*" In Development and Learning and Epigenetic Robotics (ICDL), 2012 IEEE International Conference on, pp. 1-8. IEEE, 2012.
16. **Tommasino, P.**, Caligiore, D., Sperati, V., Baldassarre, G. "*A McKibben muscle arm learning equilibrium postures.*" In Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS & EMBS International Conference on, pp. 1229-1234. IEEE, 2012.

Bibliography

- [1] Jean Massion, Alexei Alexandrov, and Alexander Frolov. Why and how are posture and movement coordinated? *Progress in brain research*, 143:13–27, 2004.
- [2] Philipp Vetter, Tamar Flash, and Daniel M Wolpert. Planning movements in a simple redundant task. *Current Biology*, 12(6):488–491, 2002.
- [3] Marjan A Admiraal, MJMAM Kusters, and SCAM Gielen. Modeling kinematics and dynamics of human arm movements. *MOTOR CONTROL-CHAMPAIGN-*, 8:312–338, 2004.
- [4] Robert Ajemian and Neville Hogan. Experimenting with theoretical motor neuroscience. *Journal of motor behavior*, 42(6):333–342, 2010.
- [5] Nikolaj A Bernstein. The co-ordination and regulation of movements. 1967.
- [6] Mark L Latash, John P Scholz, and G Schoner. Toward a new theory of motor synergies. *MOTOR CONTROL-CHAMPAIGN-*, 11(3):276, 2007.
- [7] Neville Hogan and Dagmar Sternad. Dynamic primitives of motor behavior. *Biological cybernetics*, pages 1–13, 2012.
- [8] Douglas Tweed and Tutis Vilis. Geometric relations of eye position and velocity vectors during saccades. *Vision research*, 30(1):111–127, 1990.
- [9] Marco Santello, Martha Flanders, and John F Soechting. Postural hand synergies for tool use. *The Journal of Neuroscience*, 18(23):10105–10115, 1998.
- [10] DG Liebermann, A Biess, J Friedman, CCAM Gielen, and T Flash. Intrinsic joint kinematic planning. i: Reassessing the listings law constraint in the control of three-dimensional arm movements. *Experimental brain research*, 171(2):139–154, 2006.
- [11] Yuri P Ivanenko, Andrea d’Avella, Richard E Poppele, and Francesco Lacquaniti. On the origin of planar covariation of elevation angles during human locomotion. *Journal of neurophysiology*, 99(4):1890–1898, 2008.
- [12] Domenico Campolo, Dino Accoto, Domenico Formica, and Eugenio Guglielmelli. Intrinsic constraints of neural origin: assessment and application to rehabilitation robotics. *Robotics, IEEE Transactions on*, 25(3):492–501, 2009.
- [13] Andrea d’Avella, Philippe Saltiel, and Emilio Bizzi. Combinations of muscle synergies in the construction of a natural motor behavior. *Nature neuroscience*, 6(3):300–308, 2003.

- [14] Lena H Ting and Jane M Macpherson. A limited set of muscle synergies for force control during a postural task. *Journal of neurophysiology*, 93(1):609–613, 2005.
- [15] Maura Casadio, Irene Tamagnone, Susanna Summa, and Vittorio Sanguineti. Neuromotor recovery from stroke: computational models at central, functional, and muscle synergy level. *Frontiers in computational neuroscience*, 7:97, 2013.
- [16] Andrea d’Avella, Laure Fernandez, Alessandro Portone, and Francesco Lacquaniti. Modulation of phasic and tonic muscle synergies with reaching direction and speed. *Journal of neurophysiology*, 100(3):1433–1454, 2008.
- [17] Tamar Flash. The control of hand equilibrium trajectories in multi-joint arm movements. *Biological cybernetics*, 57(4):257–274, 1987.
- [18] Emmanuel Guigon, Pierre Baraduc, and Michel Desmurget. Computational motor control: redundancy and invariance. *Journal of neurophysiology*, 97(1):331–347, 2007.
- [19] FA Mussa-Ivaldi, P Morasso, and R Zaccaria. Kinematic networks. *Biological cybernetics*, 60(1):1–16, 1988.
- [20] Vishwanathan Mohan, J Zenzeri, P Morasso, and G Metta. Equilibrium point hypothesis revisited: Advances in the computational framework of passive motion paradigm. In *Advanced Computational Motor Control Conference*, volume 9, 2009.
- [21] Vishwanathan Mohan and Pietro Morasso. Passive motion paradigm: an alternative to optimal control. *Frontiers in neurorobotics*, 5(4):1–28, 2011.
- [22] Tamar Flash, Yaron Meirovitch, and Avi Barliya. Models of human movement: Trajectory planning and inverse kinematics studies. *Robotics and Autonomous Systems*, 61(4):330–339, 2013.
- [23] Tamar Flash and Neville Hogan. The coordination of arm movements: an experimentally confirmed mathematical model. *The journal of Neuroscience*, 5(7):1688–1703, 1985.
- [24] Yoji Uno, Mitsuo Kawato, and Rika Suzuki. Formation and control of optimal trajectory in human multijoint arm movement. *Biological cybernetics*, 61(2):89–101, 1989.
- [25] Christopher M Harris and Daniel M Wolpert. Signal-dependent noise determines motor planning. *Nature*, 394(6695):780–784, 1998.
- [26] Emanuel Todorov and Michael I Jordan. Optimal feedback control as a theory of motor coordination. *Nature neuroscience*, 5(11):1226–1235, 2002.
- [27] John M Hollerbach and Tamar Flash. Dynamic interactions between limb segments during planar arm movement. *Biological cybernetics*, 44(1):67–77, 1982.
- [28] Christopher G Atkeson and John M Hollerbach. Kinematic features of unrestrained vertical arm movements. *The Journal of neuroscience*, 5(9):2318–2330, 1985.
- [29] Michel Taïx, Minh Tuan Tran, Philippe Souères, and Emmanuel Guigon. Generating human-like reaching movements with a humanoid robot: A computational approach. *Journal of Computational Science*, 4(4):269–284, 2013.

- [30] Steven Knight Charles. *It's all in the wrist: a quantitative characterization of human wrist control*. PhD thesis, Massachusetts Institute of Technology, 2008.
- [31] James D English and Anthony A Maciejewski. On the implementation of velocity control for kinematically redundant manipulators. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 30(3):233–237, 2000.
- [32] Jason J Kutch, Arthur D Kuo, Anthony M Bloch, and William Z Rymer. Endpoint force fluctuations reveal flexible rather than synergistic patterns of muscle cooperation. *Journal of neurophysiology*, 100(5):2455–2471, 2008.
- [33] Shota Hagio and Motoki Kouzaki. Recruitment of muscle synergies is associated with endpoint force fluctuations during multi-directional isometric contractions. *Experimental brain research*, 233(6):1811–1823, 2015.
- [34] Aymar de Rugy, Mark R Hinder, Daniel G Woolley, and Richard G Carson. The synergistic organization of muscle recruitment constrains visuomotor adaptation. *Journal of neurophysiology*, 101(5):2263–2269, 2009.
- [35] Steven K Charles and Neville Hogan. The curvature and variability of wrist and arm movements. *Experimental brain research*, 203(1):63–73, 2010.
- [36] Emmanuel Guigon. Active control of bias for the control of posture and movement. *Journal of neurophysiology*, 104(2):1090–1102, 2010.
- [37] James S Frank and Marie Earl. Coordination of posture and movement. *Physical therapy*, 70(12):855–863, 1990.
- [38] Daniel M Wolpert. Computational approaches to motor control. *Trends in cognitive sciences*, 1(6):209–216, 1997.
- [39] Bruno Siciliano and Oussama Khatib. *Springer handbook of robotics*. Springer Science & Business Media, 2008.
- [40] Vladimir G Ivancevic and Tijana T Ivancevic. *Natural biodynamics*, volume 27. World Scientific, 2005.
- [41] Michael I Jordan and Daniel M Wolpert. Computational motor control, 1999.
- [42] FMMO Campos and JMF Calado. Approaches to human arm movement control: a review. *Annual reviews in control*, 33(1):69–77, 2009.
- [43] Michael T Turvey. Action and perception at the level of synergies. *Human movement science*, 26(4):657–697, 2007.
- [44] JD Crawford, JC Martinez-Trujillo, and EM Klier. Neural control of three-dimensional eye and head movements. *Current opinion in neurobiology*, 13(6):655–662, 2003.
- [45] M Ceylan, DYP Henriques, DB Tweed, and JD Crawford. Task-dependent constraints in motor control: pinhole goggles make the head move like an eye. *The Journal of Neuroscience*, 20(7):2719–2730, 2000.
- [46] Domenico Campolo, Domenico Formica, Eugenio Guglielmelli, and Flavio Keller. Kinematic analysis of the human wrist during pointing tasks. *Experimental brain research*, 201(3):561–573, 2010.

- [47] WP Medendorp, JD Crawford, DYP Henriques, JAM Van Gisbergen, and CCAM Gielen. Kinematic strategies for upper arm–forearm coordination in three dimensions. *Journal of neurophysiology*, 84(5):2302–2316, 2000.
- [48] Steven Ewart, Stephanie M Hynes, Warren G Darling, and Charles Capaday. A donders like law for arm movements: The signal not the noise. *Frontiers in human neuroscience*, 10, 2016.
- [49] F Lacquaniti and R Caminiti. Visuo-motor transformations for arm reaching. *European Journal of Neuroscience*, 10:195–203, 1998.
- [50] Michel Desmurget, Hélène Gréa, and C Prablanc. Final posture of the upper limb depends on the initial position of the hand during prehension movements. *Experimental brain research*, 119(4):511–516, 1998.
- [51] CCAM Gielen, EJ Vrijenhoek, T Flash, and SFW Neggers. Arm position constraints during pointing and reaching in 3-d space. *Journal of neurophysiology*, 78(2):660–673, 1997.
- [52] John F Soechting, Christopher A Buneo, Uta Herrmann, and Martha Flanders. Moving effortlessly in three dimensions: does donders’ law apply to arm movement? *The Journal of Neuroscience*, 15(9):6271–6280, 1995.
- [53] Agnes MF Wong. Listing’s law: clinical significance and implications for neural control. *Survey of ophthalmology*, 49(6):563–575, 2004.
- [54] Tzila Shamir and Yosef Yomdin. Repeatability of redundant manipulators: Mathematical solution of the problem. *IEEE Transactions on Automatic Control*, 33(11):1004–1009, 1988.
- [55] Ferdinando A Mussa-Ivaldi and Neville Hogan. Integrable solutions of kinematic redundancy via impedance control. *The International Journal of Robotics Research*, 10(5):481–491, 1991.
- [56] Menashe Dornay, Yoji Uno, Mitsuo Kawato, and Ryoji Suzuki. Minimum muscle-tension change trajectories predicted by using a 17-muscle model of the monkey’s arm. *Journal of Motor Behavior*, 28(2):83–100, 1996.
- [57] John P Scholz and Gregor Schöner. The uncontrolled manifold concept: identifying control variables for a functional task. *Experimental brain research*, 126(3):289–306, 1999.
- [58] Stephen H Scott. Optimal feedback control and the neural basis of volitional motor control. *Nature Reviews Neuroscience*, 5(7):532–546, 2004.
- [59] Emanuel Todorov, Weiwei Li, and Xiuchuan Pan. From task parameters to motor synergies: A hierarchical framework for approximately optimal control of redundant manipulators. *Journal of robotic systems*, 22(11):691–710, 2005.
- [60] Kiisa C Nishikawa, Sara T Murray, and Martha Flanders. Do arm postures vary with the speed of reaching? *Journal of Neurophysiology*, 81(5):2582–2586, 1999.
- [61] Isaac Kurtzer, Troy M Herter, and Stephen H Scott. Random change in cortical load representation suggests distinct control of posture and movement. *Nature neuroscience*, 8(4):498–504, 2005.

- [62] Domenico Campolo, Ferdinan Widjaja, Mohammad Esmaili, and Etienne Burdet. Pointing with the wrist: a postural model for donders law. *Experimental brain research*, 212(3):417–427, 2011.
- [63] Paolo Tommasino and Domenico Campolo. Human-like pointing strategies via non-linear inverse optimization. In *2016 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, pages 930–935. IEEE, 2016.
- [64] Vincent De Sapio, James Warren, and Oussama Khatib. Predicting reaching postures using a kinematically constrained shoulder model. In *Advances in robot kinematics*, pages 209–218. Springer, 2006.
- [65] Holk Cruse, Erhard Wischmeyer, Michael Brüwer, Peter Brockfeld, and A Dress. On the cost functions for the control of the human arm movement. *Biological Cybernetics*, 62(6):519–528, 1990.
- [66] Oussama Khatib, James Warren, Vincent De Sapio, and Luis Sentis. Human-like motion from physiologically-based potential energies. In *On advances in robot kinematics*, pages 145–154. Springer, 2004.
- [67] Frouke Hermens and Stan Gielen. Posture-based or trajectory-based movement planning: a comparison of direct and indirect pointing movements. *Experimental brain research*, 159(3):340–348, 2004.
- [68] Gerald E Loeb. Optimal isnt good enough. *Biological cybernetics*, 106(11-12):757–765, 2012.
- [69] Gowrishankar Ganesh, Masahiko Haruno, Mitsuo Kawato, and Etienne Burdet. Motor memory and local minimization of error and effort, not global optimization, determine motor behavior. *Journal of neurophysiology*, 104(1):382–390, 2010.
- [70] A Aldo Faisal, Luc PJ Selen, and Daniel M Wolpert. Noise in the nervous system. *Nature reviews neuroscience*, 9(4):292–303, 2008.
- [71] Daniel M Wolpert and Zoubin Ghahramani. Computational principles of movement neuroscience. *nature neuroscience*, 3:1212–1217, 2000.
- [72] Jean-Jacques E Slotine and Weiping Li. On the adaptive control of robot manipulators. *The international journal of robotics research*, 6(3):49–59, 1987.
- [73] Mitsuo Kawato. Internal models for motor control and trajectory planning. *Current opinion in neurobiology*, 9(6):718–727, 1999.
- [74] Reza Shadmehr and Ferdinando A Mussa-Ivaldi. Adaptive representation of dynamics during learning of a motor task. *The Journal of Neuroscience*, 14(5):3208–3224, 1994.
- [75] Alejandro Melendez-Calderon, Lorenzo Masia, Roger Gassert, Giulio Sandini, and Etienne Burdet. Force field adaptation can be learned using vision in the absence of proprioceptive error. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 19(3):298–306, 2011.

- [76] Michele F Rotella, Margaret Koehler, Ilana Nisky, Amy J Bastian, and Allison M Okamura. Adaptation to visuomotor rotation in isometric reaching is similar to movement adaptation. In *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*, pages 1–6. IEEE, 2013.
- [77] Paolo Tommasino, Alejandro Melendez-Calderon, Etienne Burdet, and Domenico Campolo. Motor adaptation with passive machines: A first study on the effect of real and virtual stiffness. *Computer methods and programs in biomedicine*, 116(2):145–155, 2014.
- [78] David W Franklin, Rieko Osu, Etienne Burdet, Mitsuo Kawato, and Theodore E Milner. Adaptation to stable and unstable dynamics achieved by combined impedance control and inverse dynamics model. *Journal of neurophysiology*, 90(5):3270–3282, 2003.
- [79] Etienne Burdet, David W Franklin, and Theodore E Milner. *Human robotics: neuromechanics and motor control*. MIT Press, 2013.
- [80] David J Ostry and Anatol G Feldman. A critical evaluation of the force control hypothesis in motor control. *Experimental Brain Research*, 153(3):275–288, 2003.
- [81] Erich Von Holst. Relations between the central nervous system and the peripheral organs. *The British Journal of Animal Behaviour*, 2(3):89–94, 1954.
- [82] D Varju. A note on the reafference principle. *Biological Cybernetics*, 63(4):315–323, 1990.
- [83] Anatol G Feldman. New insights into action–perception coupling. *Experimental Brain Research*, 194(1):39–58, 2009.
- [84] Emilio Bizzi, Ferdinando A Mussa-Ivaldi, and Simon Giszter. Computations underlying the execution of movement: a biological perspective. *Science*, 253(5017):287–291, 1991.
- [85] Reza Shadmehr. The equilibrium point hypothesis for control of movement. *Baltimore, MD: Department of Biomedical Engineering, Johns Hopkins University*, 1998.
- [86] Hiroaki Gomi and Mitsuo Kawato. Equilibrium-point control hypothesis examined by measured arm stiffness during multijoint movement. *Science*, 272(5258):117–120, 1996.
- [87] Pietro Morasso, Maura Casadio, Vishwanathan Mohan, and Jacopo Zenzeri. A neural mechanism of synergy formation for whole body reaching. *Biological cybernetics*, 102(1):45–55, 2010.
- [88] Jörn Diedrichsen, Reza Shadmehr, and Richard B Ivry. The coordination of movement: optimal feedback control and beyond. *Trends in cognitive sciences*, 14(1):31–39, 2010.
- [89] Holk Cruse. The evolution of cognitiona hypothesis. *Cognitive Science*, 27(1):135–155, 2003.

- [90] Pietro G Morasso and Vittorio Sanguineti. Representation of space and time in motor control. In *Prerational Intelligence: Adaptive Behavior and Intelligent Systems Without Symbols and Logic, Volume 1, Volume 2 Prerational Intelligence: Interdisciplinary Perspectives on the Behavior of Natural and Artificial Systems, Volume 3*, pages 472–509. Springer, 2000.
- [91] Paolo Tommasino and Domenico Campolo. Task-space separation principle: a force-field approach to motion planning for redundant manipulators. *Bioinspiration & Biomimetics*, 12(2):026003, 2017.
- [92] Dragomir N Nenchev. Redundancy resolution through local optimization: A review. *Journal of robotic systems*, 6(6):769–798, 1989.
- [93] Adi Ben-Israel and Thomas NE Greville. *Generalized inverses: theory and applications*, volume 15. Springer Science & Business Media, 2003.
- [94] Alexander Dietrich, Christian Ott, and Alin Albu-Schäffer. An overview of null space projections for redundant, torque-controlled robots. *The International Journal of Robotics Research*, 34(11):1385–1400, 2015.
- [95] Pasquale Chiacchio, Stefano Chiaverini, Lorenzo Sciavicco, and Bruno Siciliano. Closed-loop inverse kinematics schemes for constrained redundant manipulators with task space augmentation and task priority strategy. *The International Journal of Robotics Research*, 10(4):410–425, 1991.
- [96] Carlos Canudas de Wit, Bruno Siciliano, and Georges Bastin. *Theory of robot control*. Springer Science & Business Media, 2012.
- [97] Richard A Berger and M Garcia-Elias. *Biomechanics of the wrist joint*. Springer, 1991.
- [98] LI Leonard, D Sirkett, G Mullineux, GEB Giddins, and AW Miles. Development of an in-vivo method of wrist joint motion analysis. *Clinical Biomechanics*, 20(2):166–171, 2005.
- [99] Mohammad Esmaeili, Sarah Moussouni, Ferdinan Widjaja, Kumudu Gamage, and Domenico Campolo. Accuracy and repeatability of parameter estimation methods from ambulatory data for the wrist joint. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 1292–1296. IEEE, 2011.
- [100] Richard M Murray, Zexiang Li, S Shankar Sastry, and S Shankara Sastry. *A mathematical introduction to robotic manipulation*. CRC press, 1994.
- [101] Vishwanathan Mohan, Pietro Morasso, Giorgio Metta, and Giulio Sandini. A biomimetic, force-field based computational model for motion planning and bi-manual coordination in humanoid robots. *Autonomous robots*, 27(3):291–307, 2009.
- [102] Steven K Charles and Neville Hogan. Dynamics of wrist rotations. *Journal of biomechanics*, 44(4):614–621, 2011.
- [103] Allan W Peaden and Steven K Charles. Dynamics of wrist and forearm rotations. *Journal of biomechanics*, 47(11):2779–2785, 2014.

- [104] Jorge Angeles and Frank C Park. Performance evaluation and design criteria. In *Springer Handbook of Robotics*, pages 229–244. Springer, 2008.
- [105] Reza Shadmehr, Jean Jacques Orban de Xivry, Minnan Xu-Wilson, and Ting-Yu Shih. Temporal discounting of reward and the cost of time in motor control. *The Journal of Neuroscience*, 30(31):10507–10516, 2010.
- [106] James E Bobrow. Optimal robot plant planning using the minimum-time criterion. *IEEE Journal on Robotics and Automation*, 4(4):443–450, 1988.
- [107] Yao-Chon Chen. Solving robot trajectory planning problems with uniform cubic b-splines. *Optimal Control Applications and Methods*, 12(4):247–262, 1991.
- [108] Alain Liegeois. Automatic supervisory control of the configuration and behavior of multibody mechanisms. *IEEE transactions on systems, man, and cybernetics*, 7(12):868–871, 1977.
- [109] Jan Peters, Michael Mistry, Firdaus Udwadia, Jun Nakanishi, and Stefan Schaal. A unifying framework for robot control with redundant dofs. *Autonomous Robots*, 24(1):1–12, 2008.
- [110] Firdaus E Udwadia and Robert E Kalaba. A new perspective on constrained motion. *Proceedings: Mathematical and Physical Sciences*, pages 407–410, 1992.
- [111] Herman Bruyninckx and Oussama Khatib. Gauss’ principle and the dynamics of redundant and constrained manipulators. In *Robotics and Automation, 2000. Proceedings. ICRA’00. IEEE International Conference on*, volume 3, pages 2563–2568. IEEE, 2000.
- [112] Cornelius Lanczos. *The variational principles of mechanics*, volume 4. Courier Corporation, 1970.
- [113] Miloš Zefran and Francesco Bullo. Lagrangian dynamics, 2005.
- [114] Oussama Khatib, Emel Demircan, Vincent De Sapio, Luis Sentis, Thor Besier, and Scott Delp. Robotics-based synthesis of human motion. *Journal of Physiology-Paris*, 103(3):211–219, 2009.
- [115] Suguru Arimoto, Masahiro Sekimoto, and Ryuta Ozawa. A challenge to bernstein’s degrees-of-freedom problem in both cases of human and robotic multi-joint movements. *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, 88(10):2484–2495, 2005.
- [116] ANDREA ZANCHETTIN. *Human-centric behaviour of redundant manipulators under kinematic control*. PhD thesis, Italy, 2012.
- [117] Hyunchul Kim, Levi Makaio Miller, Nancy Byl, Gary M Abrams, and Jacob Rosen. Redundancy resolution of the human arm and an upper limb exoskeleton. *IEEE Transactions on Biomedical Engineering*, 59(6):1770–1779, 2012.
- [118] C Karen Liu, Aaron Hertzmann, and Zoran Popović. Learning physics-based motion style with nonlinear inverse optimization. *ACM Transactions on Graphics (TOG)*, 24(3):1071–1081, 2005.

- [119] Carlo L Bottasso, Alessandro Croce, Luca Ghezzi, and Paolo Faure. On the solution of inverse dynamics and trajectory optimization problems for multibody systems. *Multibody System Dynamics*, 11(1):1–22, 2004.
- [120] Weiwei Li, Emanuel Todorov, and Dan Liu. Inverse optimality design for biological movement systems. In *World Congress*, volume 18, 2011.
- [121] Matthew Howard, Stefan Klanke, Michael Gienger, Christian Goerick, and Sethu Vijayakumar. A novel method for learning policies from variable constraint data. *Autonomous Robots*, 27(2):105–121, 2009.
- [122] Mrinal Kalakrishnan, Peter Pastor, Ludovic Righetti, and Stefan Schaal. Learning objective functions for manipulation. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, pages 1331–1336. IEEE, 2013.
- [123] Matthew C Tresch, Vincent CK Cheung, and Andrea d’Avella. Matrix factorization algorithms for the identification of muscle synergies: evaluation on simulated and experimental data sets. *Journal of neurophysiology*, 95(4):2199–2212, 2006.
- [124] Scott L Delp, Anita E Grierson, and Thomas S Buchanan. Maximum isometric moments generated by the wrist muscles in flexion-extension and radial-ulnar deviation. *Journal of biomechanics*, 29(10):1371–1375, 1996.
- [125] Donna S Hoffman and Peter L Strick. Step-tracking movements of the wrist. iv. muscle activity associated with movements in different directions. *Journal of Neurophysiology*, 81(1):319–333, 1999.
- [126] Aymar de Rugy, Rahman Davoodi, and Timothy J Carroll. Changes in wrist muscle activity with forearm posture: implications for the study of sensorimotor transformations. *Journal of neurophysiology*, 108(11):2884–2895, 2012.
- [127] Yifeng Li and Alioune Ngom. The non-negative matrix factorization toolbox for biological data mining. *Source code for biology and medicine*, 8(1):1, 2013.
- [128] Steven K Charles and Neville Hogan. Stiffness, not inertial coupling, determines path curvature of wrist motions. *Journal of neurophysiology*, 107(4):1230–1240, 2012.
- [129] Toshio Tsuji, Pietro G Morasso, Kazuhiro Goto, and Koji Ito. Human hand impedance characteristics during maintained posture. *Biological cybernetics*, 72(6):475–485, 1995.
- [130] Eric J Perreault, Robert F Kirsch, and Patrick E Crago. Multijoint dynamics and postural stability of the human arm. *Experimental brain research*, 157(4):507–517, 2004.
- [131] Keng Peng Tee, Etienne Burdet, Chee-Meng Chew, and Theodore E Milner. A model of force and impedance in human arm movements. *Biological cybernetics*, 90(5):368–375, 2004.
- [132] CR Dohrmann, HR Busby, and DM Trujillo. Smoothing noisy data using dynamic programming and generalized cross-validation. *Journal of biomechanical engineering*, 110(1):37–41, 1988.

- [133] Jun Nakanishi, Rick Cory, Michael Mistry, Jan Peters, and Stefan Schaal. Operational space control: A theoretical and empirical comparison. *The International Journal of Robotics Research*, 27(6):737–757, 2008.
- [134] Michael Mistry and Stefan Schaal. Representation and control of the task space in humans and humanoid robots. 2015.
- [135] Isaac Kurtzer, Paul A DiZio, and James R Lackner. Adaptation to a novel multi-force environment. *Experimental brain research*, 164(1):120–132, 2005.
- [136] Allan W Peaden. Dynamics and control of wrist and forearm movements. 2013.
- [137] Reza Shadmehr. Distinct neural circuits for control of movement vs. holding still. *Journal of Neurophysiology*, pages jn-00840, 2017.
- [138] John F Kalaska, DA Cohen, Martha L Hyde, and Michel Prud’homme. A comparison of movement direction-related versus load direction-related activity in primate motor cortex, using a two-dimensional reaching task. *The Journal of neuroscience*, 9(6):2080–2102, 1989.
- [139] Christian Ethier, Laurent Brizzi, Warren G Darling, and Charles Capaday. Linear summation of cat motor cortex outputs. *The Journal of neuroscience*, 26(20):5574–5581, 2006.
- [140] Tyson N Aflalo and Michael SA Graziano. Partial tuning of motor cortex neurons to final posture in a free-moving paradigm. *Proceedings of the National Academy of Sciences of the United States of America*, 103(8):2909–2914, 2006.
- [141] Michael SA Graziano, Charlotte SR Taylor, Tirin Moore, and Dylan F Cooke. The cortical control of movement revisited. *Neuron*, 36(3):349–362, 2002.
- [142] Michael Graziano. The organization of behavioral repertoire in motor cortex. *Annu. Rev. Neurosci.*, 29:105–134, 2006.
- [143] Charles Capaday, Christian Ethier, Carl Van Vreeswijk, and Warren G Darling. On the functional organization and operational principles of the motor cortex. *Motor Cortex Microcircuits (Frontiers in Brain Microcircuits Series)*, page 44, 2015.
- [144] Apostolos P Georgopoulos, Andrew B Schwartz, Ronald E Kettner, et al. Neuronal population coding of movement direction. *Science*, 233(4771):1416–1419, 1986.
- [145] Andrew B Schwartz. Useful signals from motor cortex. *The Journal of physiology*, 579(3):581–601, 2007.
- [146] John F Kalaska, Stephen H Scott, Paul Cisek, and Lauren E Sergio. Cortical control of reaching movements. *Current opinion in neurobiology*, 7(6):849–859, 1997.
- [147] Aaron D’Souza, Sethu Vijayakumar, and Stefan Schaal. Learning inverse kinematics. In *Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on*, volume 1, pages 298–303. IEEE, 2001.
- [148] Ganghua Sun and Brian Scassellati. Reaching through learned forward model. In *Humanoid Robots, 2004 4th IEEE/RAS International Conference on*, volume 1, pages 93–112. IEEE, 2004.

- [149] András Pellionisz and Rodolfo Llinás. Tensorial approach to the geometry of brain function: cerebellar coordination via a metric tensor. *Neuroscience*, 5(7):1125–1136, 1980.
- [150] Tong Lin and Hongbin Zha. Riemannian manifold learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(5):796–809, 2008.
- [151] Deva Ramanan and Simon Baker. Local distance functions: A taxonomy, new algorithms, and an evaluation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(4):794–806, 2011.
- [152] Liana E Brown, David A Rosenbaum, and Robert L Sainburg. Limb position drift: implications for control of posture and movement. *Journal of Neurophysiology*, 90(5):3105–3118, 2003.
- [153] J Smeets, J van den Dobbela, R van Beers, and Eli Brenner. Movement drift is the result of optimal sensory combination. *Adv Comp Motor Contr IIISoc Neurosci*, San Diego, CA, 2005.
- [154] Paolo Tommasino, Asif Hussain, Aamani Budhota, Charmayne ML Hughes, Wayne Dailey, and Domenico Campolo. feel the painting: a clinician-friendly approach to programming planar force fields for haptic devices. In *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*, pages 163–168. IEEE, 2015.
- [155] Domenico Campolo, Paolo Tommasino, Kumudu Gamage, Julius Klein, Charmayne ML Hughes, and Lorenzo Masia. H-man: A planar, h-shape cabled differential robotic manipulandum for experiments on human motor control. *Journal of neuroscience methods*, 235:285–297, 2014.
- [156] Paolo Tommasino, Lorenzo Masia, Welihena GKC Gamage, Azhar Muhammad, Charmayne ML Hughes, and Domenico Campolo. H-man: Characterization of a novel, portable, inexpensive planar robot for arm rehabilitation. In *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, pages 175–180. IEEE, 2014.
- [157] Gia-Hoang Phan, Clint Hansen, Paolo Tommasino, Asif Hussain, and Domenico Campolo. Instrumentation of a hand-held power tool for capturing dynamic interaction during finishing tasks. In *2016 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, pages 906–911. IEEE, 2016.