Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Computational Approaches to Human Arm Movement Control – A Review

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Abstract: Human arm movement control theories are reviewed in the current paper. The motor planning problem stated as a generation of a time plan for the execution of a movement task, is a major concern of the current paper. It will be suggested that computational models of motor control have a strong potential for the use in the area of human motor rehabilitation. Their use can be discriminated in three main areas of application: the generation of correct trajectories to be demonstrated to human subjects during physiotherapy; the assessment of motion disorders and movement quality; and the devising of challenging interaction exercises to promote recovery.

1. INTRODUCTION

This paper will review the major theories pointed out for the purpose of describing human arm movement control. In particular, computational theories are presented, that is, mathematical models for motor control that can be simulated in a computer and compared against measured data. The aim of this paper is to extract knowledge from these theories that can be useful for the purpose of research in the field of motor rehabilitation.

Human arm motor control has been an issue of investigation for several decades, during which some issues have been identified as themes of high interest (Flash and Sejnowski, 2001). Among these are problems such as planning, execution and learning. In a broad sense, the motor control problem can be stated as the generation of the muscle activations that best fit the purpose of a movement or manipulation task, given the proprioceptive and external world information available through the body sensors. The complexity of the motor control problem is strongly due to the redundancy of the human motor system as well as the redundant nature of movement tasks.

Even in a simple task such as reaching a target in free space, a multitude of possible solutions are available, each one being a path that takes the hand from the initial to the final position. Infinite solutions exist not only for this path but also for the velocity profile used to track it.

The freedom to choose both the path and the velocity profile defines the underlying redundancy in a movement task. However, redundancy arises not only in the nature of movement tasks but also as an intrinsic and beneficial feature of the human body, which provides for more flexibility to carry complex tasks. One aspect of this redundancy results from the 7 degrees of freedom (DOF) of the kinematic structure of the human arm, which exceeds the minimum necessary number (6 DOF) to move the hand in the three dimensional space (Guigon *et al.*, 2007). The problem of kinematic redundancy was first pointed by Bernstein (1967), and labelled the DOF problem. In the perspective of computational modelling, the kinematic redundancy is viewed as a problem since most hand positions can be achieved by infinite combinations of the joints. The number of possible solutions for movement planning increases further if it is considered muscle commands as and additional variable to be predicted by the theoretical models for motor planning. In fact, due to the muscle configuration in human arm, several muscles are involved in each joint movement and, therefore, it is possible to imagine different combinations of muscle activations that produce the same torque (Wolpert, 1997).

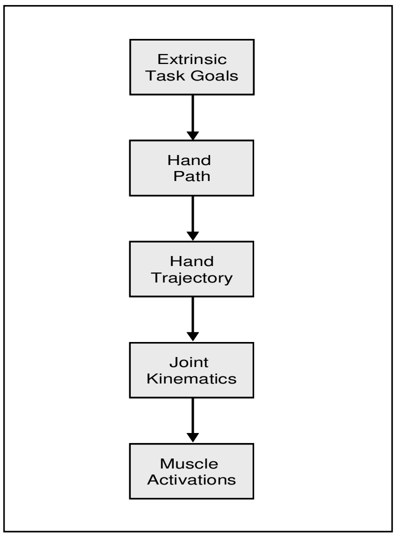

Fig.1. Hierarchical levels of specification for a movement.

These redundancy issues define sub-problems in motor control theories that are interrelated according to a hierarchy as depicted in Fig. 1. Even though the structure of this hierarchy is consensual, the sequence by which sub-problems are solved is conceived differently by different models. Some trajectory formation models postulate that the different levels of redundancy can be solved independently and usually focus only on the hand trajectory planning.

Other models are formulated on the basis that these problems are solved interactively and simultaneously. This difference defines the first major line separating motor control theories, as stated in Todorov and Jordan (1998). Since the former theories ignore the musculoskeletal system that is under control, it is accepted that these can not aim at explaining completely the underlying biologic principles that give rise to the apparent behaviour. Instead they have the less ambitious goal of providing algorithms which produce trajectories that fit well with the observed behaviour. These theories can therefore be called *Descriptive Models*. The latter theories provide computational models which embody all the fundamental processes carried out by the CNS (Central Nervous System) to produce movement. These models can be assigned the label *Complete Models*.

In spite of the complexity that the number of redundancy levels suggests, humans show amazingly regularities when generating movement. The strong experimental evidence for such regularities as lead researchers to believe that one unifying principle might be used by humans to resolve redundancy and would underlie the observed consistency in behaviour. The history of motor control research as therefore been marked by a search for this unifying principle. Early researchers have focused directly on the kinematic regularities, developing theories that were expressed in terms of the kinematic variables and therefore fall under the *Descriptive Models* class.

Although they showed high predictive accuracy in free movement, these models were weak in accounting for tasks where external forces were present. This inconsistency in *Descriptive Models* led researchers to turn to dynamic variables to find a unifying principle that would fit a broader range of movements. In accounting for the dynamics of the arm, these models did address all levels of redundancy, therefore falling under the *Complete Models* category. Within this category, the first influential model hypothesised that the minimisation of torque change was the principle underlying movement invariants (Uno *et al*. 1989). Because this and subsequent theories introduced dynamic variables in the optimization procedure, they are known as *Dynamic Models*.

A major breakthrough in understanding the nature of human motor control was introduced by Harris and Wolpert (1998), who suggested that noise in control signals within the sensorimotor loop was a determinant factor in overall motor behaviour. The theories that account for this factor are referred to in this paper as S*tochastic Models*. As more complex movement tasks, such as in visually distorted experiments or movement in different dynamic environments, were confronted with the existing models, the limitations of these became evident, notably the neglect of visually feedback or the lack of a mechanism of adaptation to different dynamics. In order to account for these phenomena, further models borrowed concepts from Control Theory to present a complete framework that would explain the success of human sensorimotor control in such a diversity of conditions (Schaal, Schweighofer, 2005). The central concept within these theories is the internal model, a computational function in the control system that represents the dynamics of the body or the environment. These theories assume that a desired trajectory is computed by a trajectory planner, and focus on how the human kinematic structure should be controlled in order to fulfil the specified task. These theories are therefore referred to as *Motor Execution Models*.

In the next two sections *Descriptive* and *Dynamic Models* will be described separately. Following that, the models for motor execution will be addressed. In the later section some considerations regarding the presented theories will be made. An in the last section some concluding remarks are provided.

2. DESCRIPTIVE MODELS

Descriptive models have the purpose of describing the apparent behaviour of human motion. Contrarily to *Complete Models* (discussed below), descriptive models do not attempt to mimic the underlying biological principles that give rise to the observed motion features. Instead, these models are computational tools that aim at providing predicted trajectories with a good match with experimental ones.

Among the empirical relations that have been identified in human arm movements are the Fitts law, the bell shaped velocity profiles in straight movements and the 2/3 power law. Fitts law concerns rapid, goal directed movements and quantifies the observed and rather intuitive relation that exists between the duration of this kind of movements with the distance and dimension of the target. Mathematically this relation is expressed as follows (Mackenzie, 1991):

$$MT = a + b \log_2(2A/W) \qquad (1)$$

where, MT = movement time, a,b = regression coefficients, A = distance of movement from start to target center and W = width of the target

The 2/3 power law states that, in curved movements, the velocity (v) is related to the inverse of the curvature radius (k) by the expression: $v(t)=\gamma k(t)^{-1/3}$, where γ is a constant factor which has been experimentally estimated as 0.33. This law basically implies that in curved movements the velocity decreases with increasing curvature. The original form of the power law has the limitation of not being applicable to paths showing straight segments or inflection points (in these cases, velocity goes to infinity). Additionally, the power law is inaccurate at low velocities and cannot predict the velocity reduction at the end of the path (Todorov and Jordan, 1998).

One common feature to the subsequent models is the use of optimal control as the strategy to mimic the biologic processes by which human motor control is achieved. It is widely accepted that optimisation provides a substantiated framework to explain human motor control because it may reproduce important biological processes, such as learning and natural evolution, that enhance behaviour much in the same way as an optimisation procedure does (Todorov and Jordan, 2002).

The optimal control methodology requires the definition of a cost function, which is based on a quantity that must be minimised in order to achieve the best performance. The cost function is usually expressed as an integral of that quantity over a period of time. The variables of interest that are used to formulate the cost function define the strategy for trajectory planning.

The bell shaped velocity profile of straight movements is one of the most consistent features of human arm behaviour. Flash and Hogan (1985) presented a model in which the reproduction of bell shaped profiles was a main concern. The authors concluded that considering smoothness of movement as the goal underlying movement control, some apparent features of arm trajectories are explained. In order to address the optimisation of smoothness, a quantitative measure of this property was adopted, which is defined as the derivative of acceleration and named as 'jerk'. Besides the bell shaped velocity profile feature, the model was also motivated by the observation that reaching movements tend to be performed in a straight fashion, regardless of the region in workspace where the movement is performed or its orientation. The fact that these position and velocity features seem to be invariant exclusively when these variables are expressed in hand coordinates (Cartesian space), lead the authors to describe minimum jerk in hand coordinates instead of joint coordinates. For the purpose of addressing planar movements, the magnitude of jerk (J) was defined as follows:

$$J = \sqrt{\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2} \tag{2}$$

and a cost function based on the square of that quantity was expressed as:

$$C = \frac{1}{2}\int_0^{t_f} \left(\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2 \right) dt \tag{3}$$

Optimal control theory was applied to this cost function, subject to the differential equations of movement and several other constraints related to the desired movement. These constraints are the initial and final positions and also the time duration (t_f) for movement execution. In curved or obstacle avoidance movements, a via-point was also specified. The differential equations of the system are simply the differential relations between position, velocity, acceleration and jerk. In that study, only planar horizontal movements were addressed namely point-to-point movements and curved unconstrained movements, which could represent obstacle avoidance situations.

Applying the optimisation procedure to the point-to-point movements, the authors fond 5^{th} order polynomials describing both x and y coordinates, which specified a straight line in space with a 4^{th} order polynomial velocity profile.

Concerning the curved movements, two 5^{th} order polynomials were derived for each coordinate, one specifying the trajectory before reaching the via-point and another for the remaining trajectory to the final position. The results of this study were extremely consistent with empirical trajectories, since the predicted point to point movements were straight lines, which is a good approximation of the roughly straight observed paths and the velocity profile is bell-shaped as empirical ones. Moreover, the predicted velocity profiles for curved movements showed a curvature-velocity relation in good agreement with empirical movements.

In a practical sense, the minimum-jerk model is very appealing due to its simplicity and the ability to predict the global features of reaching movements. However, this model shows inaccuracy when applied in particular situations, namely curved movements and through point movements (Todorov and Jordan, 1998). Noting that this model may fail to predict the movement path but is accurate in predicting the velocity profile, Todorov and Jordan (1998) presented a variation on this model, called constrained minimum jerk model. This model requires that the movement path be predefined and focuses on the generation of the velocity profile. Contrarily to the original minimum jerk model, it does not aim at predicting the path but only the velocity profile. In this aspect, this model is similar to the 2/3 power law, since both predict the velocity, for a given hand path. This model proposes to minimize the following cost function:

$$J = \int_0^{t_f} \left\| \frac{d^3}{dt^3} r[s(t)] \right\|^2 dt \tag{4}$$

where $r(s)$ is the coordinate vector of the path points and $s(t)$ is the distance travelled along the path. According to the given cost function, the purpose of the model is to minimize jerk under the constraint of a path that is pre-defined. The model was applied to a number of experimental and simulated tasks which evidenced the similarities in speed profiles obtained with this model and the 2/3 power law. However, this model showed globally better performance and was intrinsically able to deal with the limitations shown by the 2/3 power law. In commenting the results of experiments, the authors mentioned above pointed the fact that the studied movements were of short duration (1-2 seconds) which may had accounted for the good accuracy of the predicted velocities. The authors also remark that the model assumes an implicit relation between path and velocity profile and thus is valid when applied to a particular movement execution but its meaning is lost if applied to an average path of a number of trials.

The above models are concerned strictly with the description of hand trajectories in space, leaving aside the problem of joint trajectories prediction. If these models are used in a complete simulation of the human arm, additional strategies must be employed in order to compute the joints values for each hand position. This problem has been addressed by different studies, which focus primarily on joint redundancy resolution. Several studies have investigated the hypotheses that joint redundancy might be simplified by Donders' law

(Marotta, 2003). Donders law was formulated to describe the redundancy resolution policy observed in the positioning of the eye. Donders' law states that any possible vector describing a rotation of the eye can not occupy an arbitrary position in space, instead it is constrained to lie in a plane. By applying this law, the number of DOF of the eye is reduced from 3 to 2 and any gazing direction is univocally related to a rotation vector of the eye. Due to the similarities of the problems (excess of DOF) and the fact that both the eye and arm are controlled by the CNS, some authors speculated that the same law might also be applicable to the positioning of the arm. This motivation led to a number of studies which explored the usability of Donders' law in the joint redundancy problem. The reported results indicate that the application of Donders' law in the arm is limited and that a more complex strategy that is yet to be identified probably is used instead (Marotta, 2003). However, in particular tasks it was observed that Donders' law was accurate, which indicated that this law may be a special case of that general strategy.

3. COMPLETE MODELS

The most influential model described in the previous section, the minimum-jerk model, relies on a cost function based on the kinematic variables to find the solution for trajectory planning. Additionally, this model focuses only on the generation of trajectories in Cartesian space, leaving open the question of how joint space redundancy is solved. Complete Models, addressed in this section, comprise theories that consider the arm dynamics and therefore include in the cost function torques and external forces values. As a consequence of dealing with the whole arm dynamics, which is non-linear and depends on joint kinematics, a by-product of the minimization of a cost function is the resolution of all levels of redundancy. *Dynamic models*, first addressed in this section, make a break from the minimum-jerk model tradition by introducing dynamic variables in the cost function. More recently, new approaches suggest that human movement can be explained more consistently within a framework where the noise in control actions (muscle commands) is considered. These models can be regarded as *Stochastic Models* and are the subject of the second subsection.

3.1 Dynamic Models

Dynamic models take into account the dynamics of the arm and focus on joint torques, external forces and motor commands (Wolpert, 1997). Three major models were presented and named, according to the variable of interest, as 'minimum torque change', 'minimum motor command change' and 'minimum commanded torque change'.

Minimum torque change model, the most influential dynamic model, was presented in Uno *et al.* (1989). The authors pointed out that kinematic models accept the improbable assumption of considering that trajectories depend solely on the initial and final positions, disregarding the physical apparatus to execute them, or the external forces. It has been suggested that movement planning should consider dynamic aspects of the arm and the task which lead the authors to test different dynamic variables inside the cost function. The torque change was accepted has the cost function variable that yields the best agreement with observed behaviour. The cost function was defined as:

$$C = \frac{1}{2}\int_0^{t_f} \sum_i \left(\frac{dz_i}{dt}\right)^2 dt \tag{5}$$

where z_i is the torque generated at joint i. This objective function was minimised under the constraints of the musculoskeletal dynamics. For the purpose of addressing planar movements, the authors approximated the arm dynamics by a two-joint planar robot dynamics, with inertial, geometric and viscosity parameters representative of the human arm characteristics. Due to the highly nonlinear nature of this system, it is much more complex to find the unique optimal trajectory in this case than in the kinematic model case, in which the system is described by linear kinematic relations. This difficulty was overcome by employing a computational iterative method to determine the optimal solution. In this method the determination of hand coordinates trajectories involves the computation of the lower level torques at the joints. This is a fundamental implication of dynamic models, in which the three levels of motor control can not be computed in isolation. Instead, the computation of the hand trajectory is embedded with the lower levels of joint trajectory and joint torque computation. As the output of the movement planning, hand trajectory, joint trajectory and torque are produced simultaneously.

A similar approach has been taken at the Virtual Soldier Research Program to solve the redundancy in joint position (Yang *et al.*, 2004a). This research group has been developing techniques for the modelling of human motion and particularly for the prediction of human postures. The proposed method consists in computing the joint positions by minimising a cost function which contemplates the major factors that come to play in a given task (Mi, 2004). This cost function is built up by the sum of particular cost functions quantifying each of the performance factors. The variables that have been considered include effort, torque, potential energy and joint displacement. The individual cost functions based on each variable are weighted and summed to build the global cost function for a task. In the studies carried out using this technique, a very complete model of the human arm was used, which allowed for the prediction of a wide range of different arm configurations (Yang et al, 2004b). However, in these studies it is not obvious how the weights should be computed in order to represent the relative importance of each performance measure in a particular task.

3.2 Stochastic Models

In spite of its simplicity and accuracy predicting planar trajectories, the kinematic minimum-jerk model was early criticised for not considering the dynamic aspects of movement tasks (Uno *et al.*, 1998). On the other hand, the dynamic models presented are not able to predict certain movement experiments and therefore are not consensual (Wolpert, 1997).

Experiments performed under visual perturbed feedback and under force fields show evidence that support kinematics approaches. It was demonstrated that when subjects are provided with visual feedback which is altered in the region between the initial and final position, they adapt the hand path in order to correct the trajectory under the new visual perspective. Kinematic approaches predict this adaptation but dynamic models do not, since in the dynamic framework the trajectory depends only on the initial and final hand positions and not on intermediate positions. Under force fields the dynamics of the arm are modified. Nevertheless humans show adaptation that allows recovering of the normal trajectories. This behaviour is in accordance with kinematic theories, which assert that the major concern in motor control is to maintain a minimum-jerk hand trajectory. Contrarily, dynamic models predict movement modifications under force fields that do not re-establish the original paths.

A different study showed behaviours that are not predicted by kinematic models (Sabes and Jordan, 1997). Experiments concerning obstacle avoidance movements showed that humans describe trajectories in which the closest point to the obstacle is achieved when the arm is in the most inertial stable position (Sabes and Jordan, 1997). This conclusion can only be produced by a model that accounts for the dynamics of the arm.

In Harris and Wolpert (1998) a different concept of movement planning was presented, which has been regarded as an integration of kinematic and dynamic concepts. Firstly, it has been suggested that movement planning does not rely on the minimisation of jerk or torque change, but on the minimisation of the final position variation. This approach also uses an optimisation procedure, taking the end-point variance as the quantity to minimise. When humans perform several trials of reaching movements, the trajectories show the well known kinematics features presented in section 2, but are never performed the same way. Harris and Wolpert (1998) point the fact that muscle commands are corrupted by noise, which explains the variation observed in repeated movements. Moreover, the noise increases linearly with the amplitude of the command signals, which implies that the minimisation of the final position variance will require not only kinematics but also dynamic adjustment. The mentioned authors show that the minimisation of final position variance will lead to the well known kinematics features of the jerk minimisation, the 2/3 power law and Fitts law.

In an opinion article on Harris and Wolpert work, Sejnowski (1998) points out some important aspects of their theory, as it is based on the maximisation of precision while previous ones focused on the maximisation of smoothness or efficiency. While the theories based on the maximisation of smoothness have strong evidences to support them, Sejnowsky (1998) states that taking the optimisation of smoothness as the only goal to human motor control is not a well-grounded explanation for the self-adaptation of the nervous system. Later, Harris and Wolpert approach was named TOPS (Task Optimization in the Presence of Signal-Dependent Noise) and applied to additional tasks, in order to validate the model in different important situations. The most successful was presented by Hamilton and Wolpert (2002) and addressed obstacle avoidance movements, in order to clarify the behaviour previously observed by Sabes and Jordan (1997). In this study, authors argue that optimisation under signal dependent noise is an extremely suitable approach to this problem. They used an optimisation procedure that aimed at minimising final position mean-square error while maintaining probability of collision with the obstacle below a specified level. It was demonstrated that this approach yields optimal trajectories in accordance with empirical ones. However, it is recognised the fact that the approach did not consider feedback. It is stated that the average optimal feedforward trajectory is the same as the average optimal feedback trajectory in the case of linear systems, but not for non-linear, such as the human arm. Apart from providing insight about obstacle avoidance movements, the mentioned study was important because it demonstrated once more that optimisation under signal dependent noise was a valuable approach to the analysis of human movement.

More recently, Todorov and Jordan (2002) presented a new theory which aimed at providing a framework to explain motor function. As in the TOPS model, the presence of noise plays a fundamental role in this theory. Not only the signal dependent noise in motor commands but also noise in sensors measurements is also accounted. A key notion introduced by this model is the use of optimal feedback control to explain motor behaviour. Previous models for motor planning assumed that planning was performed before execution, and movements were carried out in a feedforward manner.

However, Todorov and Jordan (2002) claim that if the movement takes long enough, which is the case in many limb movement tasks, feedback is important. Moreover, feedforward strategies fail to explain on line corrections taken by humans when execution conditions change unexpectedly. In the view of these facts, a feedback optimal control method where trajectory planning and execution is assumed to take place simultaneously, have been presented. A second fundamental feature of this model is concerned with the integration of motor planning, coordination and redundancy resolution in the same approach. The authors' findings regarding coordination and redundancy resolution were summarised in what they called the 'minimum intervention principle'. Due to the redundancy in the human arm, a task can be achieved by a variety of possible arm postures. This fact can also be described as the dimension of the control space being larger than the task space.

The minimal intervention principle states that the control system will only correct deviations in the task-relevant directions of the control space. The existence of a subspace that is not relevant to the task allows feedback to be focused on the important degrees of freedom while variability may accumulate in the degrees of freedom less relevant for each particular task. Since a movement between desired points can be performed through different paths, there is also redundancy in hand trajectory to achieve a given task. Todorov and Jordan (2002) demonstrate that optimal feedback can also take advantage of this redundancy, in a similar manner to what happens in empirical trajectories. Results showed that optimal feedback predicted a reduction of variance near the desired positions (via-point and end point) at the expense of increasing variance along alternative regions of the path. These regions act like variability buffers, which is acceptable since no specified desired position was defined for them.

4. MOTOR EXECUTION MODELS

A level below trajectory planning lays the problem of motor execution, which is concerned with the computation of proper motor commands to achieve a desired task. *Descriptive Models* generate a trajectory defined by a time history of positions and velocities which later must be converted to actual torques for execution. In these models it is assumed that the trajectory is passed on to a lower level controller which is responsible for commanding the motor apparatus to follow the desired path. For this purpose, the minimum jerk model was associated with the equilibrium point model for joint control (Flash, 1987).

The equilibrium point model assumes that there is a desired position for the hand, named equilibrium position, towards which the actual hand position is attracted by means of a low level controller. This controller generates spring-damper forces related to the displacements around the equilibrium position. In order to generate movements, the equilibrium position is changed over time, along the trajectory previously planned. This concept was able to predict the slight curvature that is observed in actual trajectories and is not predicted in the minimum-jerk trajectory.

Dynamic and stochastic models rely on optimisation procedures that include all levels of motor control. Therefore motor execution is implicitly included. However, there are substantial differences between the optimal models presented before. While the TOPS model performs optimization in a feedforward fashion, the model introduced by Todorov and Jordan (2002) includes optimal feedback control. This means that the former is primarily concerned with trajectory planning, while the latter is adequate for planning and execution simultaneously.

Even though the TOPS model is not suited for movement execution, Wolpert and colleagues have presented several studies on this issue, based on the concept of internal models (Wolpert *et al.*, 1998b). Internal models in the brain are neural mechanisms that mimic the behaviour of a natural process. The suggestion of internal models in the brain was first proposed by Ito (1970) and later adopted by computational neuroscientists who integrated the concept their motor control models (Kawato, 1999; Shadmehr and Krakauer, 2008). Internal models may be discriminated in two categories, which play different roles in motor control: forward internal models can predict sensory consequences from outgoing motor commands; inverse internal models, on the other hand, may be used to compute the necessary feedforward motor commands to achieve a desired state. In other words one may say that forward models represent the causal flow in the modelled process, that is, they accept action inputs and output the predicted state; contrarily, inverse models invert the causal flow of the process, accepting the current and desired states and outputting the necessary actions to achieve the latter.

Forward models are considered essential to overcome important limitations of the physiological motor system. Signals from sensors show long delays that would make feedback control impractical, especially in fast movements.

The solution that has been hypothesised to explain how instability is avoided under sensory delays states that forward models are used to predict sensory outcome. In this sense, forward models would be integrated in a motor control algorithm having the structure of a Smith Predictor (Miall *et al.,* 1993). As described in Fig 2.a, the forward model uses a copy of the motor commands to predict the outcome state of the present action, which is used as a fast feedback signal for closed loop control. The predicted state is also sent through an 'output forward model' which simulates delays in sensory signals, making the predicted state synchronized with actual sensory information for comparison. This error is fed back as correction for disturbances affecting the system, which is unavoidably delayed.

Inverse internal models have also been pointed out as necessary to perform fast movements Wolpert *et al.* (1998b). When rapidly reaching for a target, delays in the feedback loop, which include not only sensory delays but also information processing and motor delays, would commit a strictly feedback strategy to failure, especially considering that high gains would be necessary in such movements. A natural way to address this problem would be to build a plan of the motor commands to apply during the whole movement, and put little emphasis on feedback information. In this case,

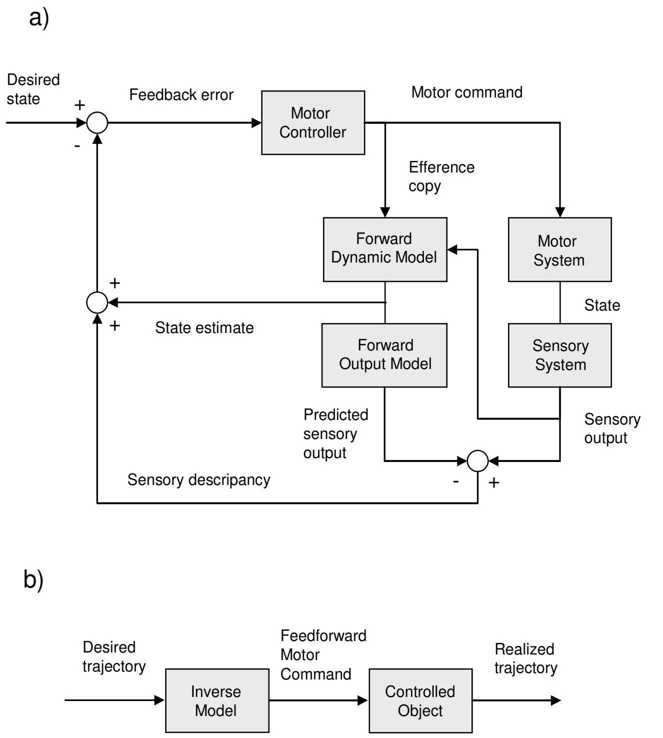

Fig. 2. Hypothesised internal models in human sensorimotor control.
a) Forward models within a Smith Predictor scheme.
b) Inverse models in feedforward commands computation.

the control strategy would be of the open loop type, with thedesired trajectory being provided to the controller and the motor commands being computed by an inverse model of the body and environment (Fig. 2.b).

An important feature of internal models is that they may represent not only the human motor apparatus but also the environment with which it is interacting. The existence of these representations would explain the high success humans show in manipulating environments in tasks as different as swimming in a pool, driving the wheel of a car, or cleaning a window. Wolpert and Kawato (1998a) suggest that there are multiple paired internal models that fit different dynamic tasks and can be combined to interact with a panoply of different situations. In that study, the authors propose an architecture, later named MOSAIC (Haruno *et al.*, 2001), for simultaneously learning the multiple inverse models necessary for control and selecting the appropriate model to deal with a given environment.

5. DISCUSSION

Computational models of motor control present a strong potential for the use in the area of human motor rehabilitation. Their use can be discriminated in three main areas of application:

1. The generation of correct trajectories to be demonstrated to human subjects during physiotherapy. The traditional approach in this matter has been the use minimum-jerk trajectories to produce the Cartesian path and velocity profiles. The drawbacks of the application of the minimum-jerk model are the requirement to provide the duration of the movement and intermediate points in the case of curved movements. The minimum jerk model is highly suited for on-line trajectory planning, due to its simplicity and closed form expression for the trajectories. Recent advances in motor control research have brought profound and striking changes to the understanding of this subject. The introduction of noise as a key factor in motor planning and optimal feedback as a well-grounded control strategy lead to theories aiming at unifying the problem of motor control. The TOPS model and optimal feedback model brought new insight to the computational perspective of motor control. These models suggest that the objective in human movement may not be gracefulness but the optimisation of more practical quantities such as precision, which as a side-effect may produce smoothness. The authors of these models also suggest that depending on the task, different quantities are probably chosen by the brain to be minimised. Moreover, the methodologies used in each model present strong consistency, since in the optimisation procedure important features of the controlled system are considered, namely its dynamics and signal noise. The current state of development of these models presents some obstacles to their application for the purpose of trajectory generation. The validity of the models has been shown in a very few situations and therefore the ambition of having trajectories for a wider range of tasks which are specified by different goals has not yet been fulfilled.

2. The assessment of motion disorders and movement quality. Both the research in computational models of motor control and in motor rehabilitation present the same need of knowing what makes the quality of movements. The authors of the TOPS model and optimal feedback model point the fact that if the quantities to optimise are known, it would be possible to predict human movements in a wider range of tasks. Presently, the study of human arm movement has been focused mainly on tasks such as reaching, drawing and obstacle avoidance. Todorov (2004) suggests that an important missing study would be the identification of the characteristics of human movement in different tasks, in a way that the quantities being optimised would be recognised. This would allow for the test and validation of computational models in a wider range of tasks. A similar need exists in motor rehabilitation research. If the quantities to be optimised in a movement are known, the measures of assessment would compare the measured values of these quantities to desired values. Despite the suggestion from computational models that human movements can be specified from objective functions expressed on the quantities to optimise, the strict range of tasks addressed to date provides little knowledge that might be useful in assessment of motor skills and deficiencies.

3. The devising of challenging interaction exercises that promotes recovery. If the human movement is viewed from the perspective of the internal models framework, some movement impairments can be compared to errors in the internal representations of the motor apparatus or the environment dynamics. If these deficiencies are identified, it should be possible to choose dynamic tasks that would stimulate the learning of the missing representations.

6. CONCLUSIONS

Recently, much research that involves VR and haptic devices has been conducted in medical rehabilitation and tele-rehabilitation to enhance patients' motor and cognitive skills, in a repetitive and progressive manner. However, there is still a gap between the design of such systems and their usage with real rehabilitation patients.

Occupational Therapists need better control and configuration of such systems in order to, for example, select the amount of time delay, angle, zoom, difficulty, and other parameters that will be used as a form of tracking the patient's progress. But more importantly, current haptic systems have hardware limitations that need to be overcome to make them practical for human motor rehabilitation.

Hence, further research is needed in this field of knowledge and the present paper aims to be a contribution for that, reviewing the control methodologies that could be applied to haptic devices developed for human motor rehabilitation.

ACKNOLEGEMENTS

Research for this paper was partially supported by Project POCTI-SFA-10-46-IDMEC of FCT, funded by POCI 2010, POSC, FSE and MCTES.

REFERENCES

Bernstein, N. (1967) The Co-ordination and Regulation of Movements. Oxford, UK. n. 97 Pergamon Press.

Flash T., Sejnowski, T.J (2001). Computational approaches to motor control. *Current Opinion in Neurobiology*, **11**, pp. 655-662.

Flash, T. and Hogan, N. (1985). The coordination of arm movements: an experimental confirmed mathematical model. *J. Neurosciences* no. 7, pp.1688-1703.

Guigon, E., Baraduc, P. and Desmurget, M. (2007) Computational Motor Control: Redundancy and Invariance. *J Neurophysiol*. n. 97, pp. 331–347.

Hamilton, F. C., Wolpert, D. M. (2002). Controlling the statistics of action: Obstacle Avoidance. *J. Neurophysiology*, vol 87, pp2434-2440.

Harris, C. M., Wolpert, D. M. (1998). Signal-dependent noise determines motor planning. *Nature*, n. 394, pp. 780-784.

Haruno M, Wolpert, D.M. and Kawato, M. (2001). MOSAIC model for sensorimotor learning and control. *Neural Computation*. n. 13, pp. 2201–2220.

Ito, M. (1970). Neurophysiological aspects of the cerebellar motor control system. *Int J Neurol*. n. 7, pp. 162-176.

Kawato, M. (1999). Internal models for motor control and trajectory planning. *Current Opinion in Neurobiology*. n. 9, pp. 718–727.

MacKenzie, S. (1991). Fitts' law as a performance model in human-computer interaction. PhD thesis.

Marotta, J. J. , Medendorp, W. P. and Crawford , J. D. (2003). Kinematic Rules for Upper and Lower Arm Contributions to Grasp Orientation. *J Neurophysiol*, n. 90, pp 3816–3827.

Mi, Z. (2004). Task based prediction of upper body motion. Phd Thesis.

Miall R. C., Weir D. J., Wolpert, D.M. and Stein, J.F. (1993). Is the Cerebellum a Smith Predictor?. *Journal of Motor Behavior*. n. 3, vol 25, pp. 203-216.

Sabes P. N., Jordan M. I. (1997). Obstacle avoidance and a perturbation sensitivity model for motor planning. *J Neuroscience* n. 17, pp. 7119-7128.

Sabes P. N., Jordan M. I. And Wolpert, D.M. (1998). The role of inertial sensitivity in motor planning. *J Neuroscience*. n. 18, pp. 5948-5957.

Schaal, S., Schweighofer, N. (2005) Computational motor control in humans and robots. *Current Opinion in Neurobiology*. n.15, pp. 675–682.

Sejnowvski, T. J. (1998). Making smooth moves. *Nature*, n. 394.

Shadmehr, R., Krakauer , J. W. (2008). A computational neuroanatomy for motor control. *Exp Brain Res*. Online Feb 5, 2008.

Todorov, E. And Jordan, M. (1998). Smoothness Maximization Along a Predefined Path Accurately Predicts the Speed Profiles of Complex Arm Movements *J.Neurophysiol*. 80: pp. 696–714.

Todorov, E. and Jordan, M. (2002). Optimal feedback control as a theory of motor coordination. *Nature*, vol. 5, n. 11.

Todorov, E. (2004). Optimality principles in sensorimotor control. Nature Neuroscience ,Vol. 7, n. 9,.

Uno, Y, Kawato, M, Suzuki R. (1989). Formation and control of optimal trajectory in human multijoint arm movement – Minimum torque change model. *Biologic cybernetics* n. 61, pp. 89-101.

Wolpert, D. (1997). Computational approaches to motor control. *Trends in cognitive sciences*. Vol. 1 n. 7.

Wolpert, D.M. and Kawato, M. (1998a). Multiple paired forward and inverse models for motor control. *Neural Networks*. n. 11, pp. 1317–1329.

Wolpert D.M., Miall R.C. and Kawato M. (1998b). Internal models in the cerebellum. *Trends in Cognitive Sciences, n. 2, pp 338-347.*

Yang, J., Abdel-Malek, K. (2004a). The Iowa Interactive Digital-Human Virtual Environment 2004 ASME International Engineering Congress. *Proc. of the 3rd Symposium on Virtual Manufacturing and Application*.

Yang, J., Marler, T., Kim, H., Arora, J.S. , Abdel-Malek, K. (2004b). Multi-Objective Optimization for Upper Body Posture Predicition. P*roc of 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*.