Journal of Control and Decision, 2016
http://dx.doi.org/10.1080/23307706.2015.1129295

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Learning control in robot-assisted rehabilitation of motor skills – a review

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(*Received 13 July 2015; accepted 3 December 2015*)

The key idea in iterative learning control is captured by the intuition of 'practice makes perfect'. The underlying learning is based on a gradient descent algorithm iteratively optimising an appropriate input–output measured criterion. How this paradigm is used to model quantitatively, at an input/output level, the learning that happens in the context of human motor skill learning is discussed in this note. Experimental studies of human motor learning, in robotically controlled environments, indicate that a model consisting of a classical (iterative) learning control augmented with an appropriate kinematic model of human motor motion fits the observed human learning behaviour well. In the context of the rehabilitation of motor skills, such models promise better human–machine interfaces that extend the capability and capacity of rehabilitation clinicians by creating effective robot–patient–clinician feedback loops. The economic promise of robot-assisted rehabilitation is to greatly extend the intervention capacity above what presently can be achieved by rehabilitation systems: addressing the needs of more people, over longer periods of time and at a distance in the comfort of their own personal environment. Moreover, the robot platforms provide for a more rigorous and quantitative evaluation of the patient's motor skill across the entire personal rehabilitation trajectory, which opens up opportunities for improved, more individually tuned rehabilitation regimes.

Keywords: human motor learning; motor adaptation; learning control; rehabilitation robots

1. Introduction

The significant miniaturisation of computing devices, sensors and actuators, enables these devices to become both more powerful and more affordable. This in turn propels inter alia the field of robotics, which consequently can play a more pervasive role in society. For an ambitious forward looking plan, see for example, the European Robot roadmap produced by EuRobotic (Bischoff et al., 2010). In particular, in the area of health services, the problems associated with partial or total loss of mobility can be addressed using robots. As identified in the roadmap (Bischoff et al., 2010), one of the key technologies that requires much further development concerns the native intelligence of robots, an issue that applies in particular to those robots that provide mobility services. Indeed the human/machine interface – the ease with which robot assist motion is smoothly and acceptably integrated into the human environment – remains unsatisfactory, and is the subject of much research. Robot learning

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is seen as a key in achieving the economic promise of robots in society, and much progress is being made with input from fields such as biomechanics, machine learning, information theory, artificial intelligence and control theory. However, it appears to us that much can be gained by achieving a better understanding of human learning in the context of motor skill learning, and to this end collaborations with clinicians and neuroscientists are essential.

In this paper, we consider in particular how learning control theory, a form of adaptive control, combined with an acceptable, approximate model of human motion, informs our understanding of human motor skill (re-)learning and how this may advance robot-assisted rehabilitation therapy.

At present rehabilitation, after say a stroke or loss of motor skill through trauma, is mainly enabled through well-trained physiotherapists. Rehabilitation treatments require a significant effort over extended periods of time to achieve adequate independence and sufficient motor skill restoration. The situation is only made more unpalatable by an actual shortage of trained therapists (Maciejasz, Eschweiler, Gerlach-Hahn, Jansen-Troy, & Leonhardt, 2014).

In view of a growing and ageing population, it comes as no surprise that the total economic burden of the society associated with motor skill loss (mainly loss in economic productivity) and the corresponding rehabilitation efforts (part of the direct carer costs) is increasing rapidly. This goes a long way towards motivating the use of robot-assisted rehabilitation; that is using robotic platforms to extend the physiotherapist's ability: to care for more people, to follow up over more extended periods of time, and to assist people at a distance, in the comfort of their own homes. The economic opportunity for robot assistance in the rehabilitation context is therefore twofold: to reduce the financial burden of direct care and to improve the economic independence of the patient and return the patient to economic independence more quickly. In general it is the economic independence that represents the greater economic opportunity in this context (Deloitte Access Economics, 2013).

We first review the state of the art in interactive technologies (either passive or active) at play in the rehabilitation of motor impairment. As it is a very wide field, we focus on technologies in the context of the upper limb, with an emphasis on the sensor, system identification, control and iterative learning aspects in particular. For a more robot devices-oriented review, classifying robots with regards to the motor impairment they address, we refer to Maciejasz et al. (2014). Another review relevant to the present paper is Basteris et al. (2014), which is perhaps not as comprehensive in its coverage of robot mechanisms as Maciejasz et al. (2014), but is more aligned with the present paper in that it focuses on the actual robotic control aspects. Under the definition of interactive technologies for rehabilitation, we include the consideration of active systems –or robots–, as well as passive systems, including passive–reactive mechanisms such as spring-loaded mechanisms that provide gravity compensation to a limb and/or resist or restrict the motion of the human limb and purely passive sensor systems coupled with virtual reality technologies. Only those technologies that involve sensors that measure some aspects of the patient's motion are considered.

Accepting that for the robots (whose low-level functions include adequate sensor fusion, motion and force control), the interesting questions concern the robot-human interaction beyond the 'robot-obvious' tasks such as tracking trajectories that form part of a rehabilitation exercise prescribed by a clinician. Indeed the mere incorporation of an (active) device in the routine of rehabilitation work does not achieve the full potential of robot assistance in the rehabilitation field. The economic gains can only be achieved through a superior, more natural human–machine interface that progresses rehabilitation in a fashion that is more independent from the clinician, while remaining to be well-tuned to the patient. The main thesis of this paper is that a model of human motor skill recovery, trained to the individual patient and integrated with the robot control algorithms, can achieve much improvement in the natural human–machine interaction within rehabilitation of motor skills.

To develop adequate learning models, the standing and reasonable assumption in the field is that human motor learning of a new task or the relearning of an old task under impaired conditions is performed in a similar manner from a learning perspective (Karniel & Inbar, 2000). In this way, working with healthy subjects through a series of well-controlled and monitored learning exercises, the motor learning process can be quantitatively modelled. These models are then transferred into the rehabilitation context. It is in the development of these models that adaptive and learning control ideas are shown to play a significant role. Although this may appear perhaps unreasonable, it should be easy to accept that learning control can model the input/output behaviour of learning in a variety of contexts, including human motor skill learning. After all, the input–output behaviour of human/animal learning served as the motivation for the development of learning control in the first place (Wiener, 1961). The relevance of iterative learning control (ILC) may well be limited to this input/output context, as there is indeed at present no basis on which to hypothesise that adaptive control or learning control as developed in the control theory realm has much relevance to describe the essence of the incredible capacity of human learning. Nevertheless as will be seen, the latter is not essential to achieve much progress in the robot-assisted rehabilitation field. Moreover, that the input/output behaviour of learning in a human motor skill context can be captured using learning control ideas is now well established in the literature (see also Zhou (2015) and its references). We review a number of experiments underpinning this assertion and also present some of our own investigations in this context. The experimental results inform appropriate computational models of human learning. In turn, these models enable the evolution of robotic assistance in the direction of extending the capacity of the clinician, through the design of a nested feedback loop involving robot, patient and therapist.

The rest of the paper is organised as follows. Section 2 contains a short review of interactive rehabilitation technologies. Section 3 reviews recent investigations to characterise human motor learning and the subsequently developed computational models of human motor learning. Section 4 discusses the use of these human learning models in the context of rehabilitation of motor impairment using the interactive technologies described earlier. The conclusion 5 points to ongoing and future work.

2. Technology-assisted rehabilitation

A brief overview of the current state-of-the-art robots used in rehabilitation therapy is provided from the control point of view. The key benefits that interactive technologies' promises are also identified. Particular attention is paid to where models of human motor learning provide or may provide a real advantage.

2.1. Rehabilitation systems

Interactive systems used in the context of motor rehabilitation, including commercially available technology as well as research and development platforms, but limited to upper limb assist devices, may be categorised as follows:

- *Passive mechanisms* fitted with a range of sensors (mainly position, displacement and inertial sensors) and often augmented with a virtual environment in the form of a game-like challenge to guide the patient through the training phase. Examples of such platforms are the commercially available AbleX (Im-Able, New Zealand), the ReJoyce (Rehabtronics, Canada) and the Armeo®Spring (Hocoma, Switzerland).

- *Robotic manipulanda* that regulate the motion at the end-effector of the robot, as well as the hand of the subject. These systems have a variety of sensors for measurement of hand motion and/or interaction forces. Examples include the commercially available InMotion ARM™(Interactive Motion Technologies, USA, derived from the MIT-Manus Hogan, Krebs, Charnnarong, Srikrishna, & Sharon, 1992) and the research platform MIME (Burgar, Lum, Shor, & Van der Loos, 2000).
- *Robotic exoskeletons* form another class of active systems. These are powered robotic mechanisms that regulate force and motion at the joint space of the subject's arm. These promise a more natural contact environment. The sensors typically include position, joint angle and torque transducers. Specific examples are the commercially available Armeo®Power (Hocoma, Switzerland, derived from the research platform Armin (Mihelj, Nef, & Riener, 2007; Nef, Mihelj, & Riener, 2007) and the ABLE platform (Garrec, Friconneau, Measson, & Perrot, 2008) as well as the exoskeletons under development by Strickland (2012) and Sugar et al. (2007).

2.2. Benefits of robot-assisted rehabilitation

Many papers have argued the merits of using robot-assisted rehabilitation (e.g. Klamroth-Marganska et al., 2014; Lo et al., 2010; Lum, Burgar, Shor, Majmundar, & Van der Loos, 2002). Nevertheless, a fully objective evaluation of efficacy is still lacking (Mehrholz, Haedrich, Platz, Kugler, & Pohl, 2012). More importantly, there is no conclusive evaluation that addresses the important question 'Does robot-assisted rehabilitation achieve superior outcomes above classical rehabilitation techniques?'.

In Klamroth-Marganska et al. (2014) the authors compare robot-assisted rehabilitation and conventional rehabilitation. The study involved 73 patients and concluded that those patients completing robotic therapy realised greater improvements in motor function. Nevertheless it also noted disappointingly that the difference between the two groups was not statistically relevant. One may take comfort in the observation that this result, also confirmed by a similar study in Lo et al. (2010), at least suggests that a robot-assisted therapy is as good as the conventional therapy. However, neither do such results encourage the pursuit of robot-assisted therapy. On closer inspection it appears that many factors that could have affected the outcome of the study were 'normalised' for the sake of providing a level playing field. For example, the length and the number of training sessions were the same for both groups.

It can be argued, however, that these normalisations have the effect of removing the greatest strength of robotics. Many questions around the impact of robot-assisted rehabilitation are phrased as if there is a competition between robotic and non-robotic rehabilitation systems, hence requiring some form of an accepted level playing field to draw a valid conclusion. Clearly such thinking defeats the purpose of introducing a robot in the rehabilitation system in the first place. Rather, we argue that for the present, in the absence of advanced robot technology that could substitute a therapist by a robot, the real objective of introducing robot-assisted rehabilitation is to improve the overall efficacy of rehabilitation through a proper design of the robot–patient–therapist feedback loop. Hence, the evaluation should focus on how and to what extent the rehabilitation outcomes are augmented and improved in the robot–patient–therapist system above the classical patient–therapist system. Also, the extent to which a lower economic burden as well as improved outcomes can be realised is extremely relevant.

Some observations on the merits of robot-assisted rehabilitation in this vein can be found in Huang and Krakauer (2009) and Casadio and Sanguineti (2012). These papers identify the strengths of the robot-assisted system as stemming from the more precise measurements and more objective assessment of the patient's progress. These advantages in turn enable the robotic system to engage the patient in a more vigorous level of physical exercise, which promises a shorter time span for a more complete rehabilitation result, with concomitant economic benefits.

2.2.1. Benefits derived from sensing rehabilitation progress

Clearly, the multitudes of sensors that are incorporated in rehabilitation robots (for their control and/or for the explicit purpose of observing the patient) provide information not available without the robot. The measurements characterise in great detail the movement as directed by the patients themselves.

In the conventional therapy, a patient's motor skill capability is assessed using standardised tests, such as the Fugl Meyer Assessment (Fugl-Meyer, Jääskö, Leyman, Olsson, & Steglind, 1974) and/or the Wolf Motor Function Test (Wolf, Lecraw, Barton, & Jann, 1989). These tests are conducted by therapists, and provide for a qualitative assessment of the motor skills. Patients are instructed to perform a motion or task and the completeness and the quality of the execution is graded on the basis of a visual inspection of the executed motion. These tests are time-consuming and rely heavily on the therapist's training and experience. The evaluation is clearly subjective and by necessity a rather coarse assessment of the actual motor skill of the patient. As a result, such assessment is performed infrequently during the rehabilitation period. It is not uncommon that there are only two formal tests, one when the patient starts with rehabilitation and one at the conclusion of the formal rehabilitation treatment. The tests are supplemented by observations made by the therapist during the rehabilitation process. Most importantly, such qualitative observations may provide but little guidance to the patient, who may become discouraged by not seeing or feeling the improvement over an extended period during rehabilitation.

In contrast, the data obtained from the patient's exercises through robot-assisted rehabilitation provide more regular information in a very quantitative manner for every rehabilitation session and during each session. Kinematic measurements capture at least a part of the current state of the patient's movement ability. Relevant metrics that may readily be derived from such measurements include the range of motion (ROM) (movement speed, acceleration, jerk and smoothness) and more generally, joint recruitment, joint range of motion and inter-joint correlation. Most of these metrics are not currently used in any rehabilitation protocol, even though many a metric has been developed and investigated within a clinical framework (de los Reyes-Guzmán et al., 2014; Kostić, Popović, & Popović, 2013). Furthermore, other variables may be inferred from measurements. For example, a motion model allows for the estimation of force profiles given the timed position and velocity measurements. More importantly, it enables the estimation of the patient's exerted force profiles, as reported in a recent study (Wu, 2015). These patient force profiles provide for an excellent assessment of the motor skill ability of the patients.

Although such observations are as yet not a part of regular clinical assessment (perhaps because of the lack of an agreed protocol), they are readily available through the use of interactive devices, and have the potential to provide great insight in the rehabilitation progress of the patient. Indeed, several recent studies demonstrated the possibility of applying movement metrics on robotic measurements in a rehabilitation context, either with planar manipulanda (Frisoli et al., 2012; Gilliaux et al., 2012) or exoskeletons (Fong, Crocher, Oetomo, & Tan, 2015). A recent review article (Nordin, Xie, & Wünsche, 2014) indicated the potential to extend the metrics even further into more coordination and planning-based measurements, which are indirect measurement of cognitive function. Also, in Casadio and Sanguineti (2012), the authors were able to capture patients' motor skill evolution during a rehabilitation process, session after session, based on simple kinematic measurements. They proposed a dynamic, iterative model of the progression of motor learning. Indeed specific kinematic metrics, derived from the regularly sampled measurements from the robotics systems during the therapy, can be used to estimate the patient's involvement in the execution of the movements. This provides feedback to patient and therapist alike, indicating the patient's current (motor function) ability. In turn, this enables more patient-specific rehabilitation programmes. Furthermore, the regular and more detailed feedback may provide additional motivation to the patient, who will see a more fine-grained progression in rehabilitation recovery, and is therefore more readily and positively challenged to improve further. Nevertheless, to reap these benefits, more work is required to provide appropriate protocols, as well as generally accepted (standardised) representations of motor skill metrics that can easily be interpreted by the therapist and by the patient.

2.2.2. *Benefits derived from robot-assisted motion*

Clearly the use of robot-assisted rehabilitation provides for more degrees of freedom, and higher repeatability in the physical interaction with the patient as compared to purely human-assisted rehabilitation. In conventional therapy, clinicians aide patient movement through providing support for their weight or by directly assisting the motion, or by restraining or correcting patient led motion. Without such supervisory assistance, the patient may not be able to produce a movement (in the early stages) or to complete the movement correctly (in the later stages), leading to a limited recovery due to limited feedback. The judiciously applied assistance by the therapist augments the successful task completion, and encourages relearning of movements through repetition and active patient involvement, within the envelope of what is feasible.

Robots have the ability to regulate forces and movements accurately and repeatably, hence are well suited to the task at hand. Given all the measurements, and with appropriate modelling and design, the control strategy can deliver a basic human–machine interaction tuned to the capability of the patient. Moreover, assistance such as weight compensation and augmented performance in a task are easily provided. Nevertheless, how to capture the desired physical interaction with the patient so as to encourage relearning of motor skills remains an active area of research. In the first instance, evolutionary progress will be made in the therapy strategies based on the improved measurement environment offered by robot-assisted rehabilitation.

The paper Basteris et al. (2014) presents a review and classification of the different types of control approaches implemented in a variety of rehabilitation robots to define an appropriate mechanical human–robot interaction. One distinguishes between assistive forces, which seek to provide the least amount of assistance required for a patient to complete the task at hand (Emken, Bobrow, & Reinkensmeyer, 2005); resistive forces, which oppose the intent of the patient in order to strengthen the muscles, and to provide endurance and achieve more finely controlled human movement; and corrective forces, which do not assist the execution of the actual, natural movement, but prevent the execution of 'incorrect' movement. Any one robot can use a mixture of assistive, resistive and corrective forces during any one exercise motion. Moreover, as will become clear in the sequel, we also see an important place for disturbing forces, forces that do not necessarily form a regular pattern, but throw the patient motion off course and require corrective intervention from the patient to restore the desired completion of the task at hand. These forces allow the therapist to explore the human motor ability in a neighbourhood of the desirable motion, and also serve to strengthen muscles that would otherwise not participate in the motion.

At present there is no universally accepted control design methodology to generate the appropriate mechanical interaction with a patient, nor how this interaction should vary over time and depend on the actual state of the patient's motor skill, so as to aid a fast rehabilitation recovery that is as complete as possible given the patient's limitations. Real patient issues such as fatigue in muscles, limitations in motion and variable stiffness make for real challenges in the control design for rehabilitation. Therapists call on their experience and judgement to suggest a plausible therapy. Different therapists may well suggest different strategies, and indeed many different strategies may lead to the same rehabilitation outcome.

Clearly, in such a context there are many difficulties for control design. First, the ultimate goal is elusive, as the patient's ultimate motor skill performance is not a well-defined object. Certainly, it is not known before rehabilitation commences. Our own motor learning experience will suggest that ultimate ability depends on the (rehabilitation) trajectory, or sequence of trials, and therefore also on the nature of the trauma (which defines the starting point for the rehabilitation process), and indeed performance may continue to improve with time and exercise. All of this suggests that a rehabilitation control task has no unique objective, but rather serves to attain an ill-defined collection of feasible or acceptable objectives.

It is in this context that an ILC paradigm, as in learning through experimentation, appears to be a natural fit. As rehabilitation progresses, we want to learn and to track the (time-varying) motor model of the patient, and learn how the patient re-learns the lost motor skills. Based on the past outcomes from the motor skill exercises, we may design in an iterative fashion: as more information about the model (patient motor skills and patient learning) becomes available, the next set of exercises and robot–patient interaction modes to reach for more improvement in motor skill rehabilitation.

The so-called windsurfer approach, see Lee, Anderson, Mareels, and Kosut (1995) and Lee, Mareels, and Anderson (2001), where in iterative fashion, identification and control designs alternate to achieve a better outcome, appears particularly well suited to the task at hand – although it will need to be suitably modified to allow explicitly for the time varying nature of the plant under control: as rehabilitation progresses so should the mobility. A well-known drawback of such methods is that in general the end-goal is not unique, and depends on the sequence of designs one has passed through, even when the underlying plant to be controlled is not changing over time (but this is also a feature of the patient–therapist rehabilitation process). Nevertheless, the methodology typically leads to significant improvement in the control objective as compared to the starting position. Moreover, perturbations in intermediate designs may be applied to explore a larger domain of the design freedom, whilst also characterising better the actual limitations of the problem at hand. The windsurfer approach is typically used with parameterised models for the control and identification task. Similar to the windsurfer approach, but focused on learning functions rather than a finite number of parameters, is the 'ILC' methodology. It has the ability to 'learn' from previous experience so as to improve overall control performance. The idea of using repetition, or practice makes perfect, underpins this method (Owens, 1977; Uchiyama, 1978). The early work by Arimoto, Kawamura, and Miyazaki (1984, 1986), Arimoto (1990), Arimoto, Naniwa, and Suzuki (1990), used the framework of contraction maps to establish how learning techniques, such as local gradient descent, converged to or learned input functions. At its heart, ILC, like all learning in essence, is a feedback based on a measurable error, the difference between what is desired and what has been achieved. (In the context of rehabilitation, what is desired is ill defined, and is itself a moving objective, depending on the amount of rehabilitation that has taken place. This makes the rehabilitation context an interesting extension of classical ILC.) Since then much research has served to expand on these ideas. Moreover the practicality of the ILC framework has been demonstrated through numerous industrial implementations. The theory is now well developed (Moore, Johnson, & Grimble, 1993; Xu & Tan, 2003). For an overview of many of the industrial applications we refer to Ahn, Chen, and Moore (2007) and Bristow, Tharayil, and Alleyne (2006).

2.3. *The need for a learning model*

From the above discussion, it transpires that in rehabilitation design, some model is required of the learning or recovery process of the patient under consideration. This is in addition to a model of the kinematics of the actual motion. A learning model will provide measures previously unavailable to therapists such as indications of the current recovery status of the patient, the patient's recovery rate or possibly some indication of how complete a recovery is possible. Moreover, such a model will provide insight as to *how* to treat the patient. That is, how the robot should be controlled, such that the patient is encouraged towards a more complete recovery in a shorter time. The design freedom may include improvements in the interaction modality (assistive, corrective, resistive, disturbing forces), excitation modality (level of forces, limitations of movement), or even changes in the overall rehabilitation strategy (temporal properties and spatial extent of the motion, timing and frequency of trials). However, this is not the only reason why a particular exercise or excitation may be selected. Indeed, in order to obtain a model of the underlying learning, and the potential capacity for improvement, some excitation will be required to build this model and to bound or to estimate in some way what motor skill ability can be relearnt. The disturbing forces are particularly useful in this context. This *dual* use of excitation (the rehabilitation exercises) – to execute the task at hand, and to learn how well the task can be executed – is a key concept in adaptive or learning methodologies (Filatov & Unbehauen, 2000).

3. Models of motor movement and learning

Models for human motor learning are difficult to obtain, as it requires one to distinguish the action of learning in the context of the human motor system that is essentially a 'time-varying, nonlinear, and many-to-one system' (Karniel & Inbar, 2000). Indeed, the human motor system includes a human motor controller acting on the human body to execute motion. In the context of rehabilitation both the controller and the human body (muscles) are undergoing significant change, or otherwise there was no rehabilitation taking place. The situation is even worse, as much of the human motor system (e.g. most of its communication infrastructure its vast array of motor and sensory neurons) is essentially not accessible for direct measurements, which are typically limited to (posture) gross motor position measurements only.

The problem posed by learning in rehabilitation is circumvented, by assuming that learning is essentially unaffected by rehabilitation (Karniel & Inbar, 2000); that is we may construct a learning model using healthy subjects, where the human motor system exhibits some stationarity and then reuse this model in the rehabilitation context. Moreover, by judiciously developing experiments we may solicit the learning response as distinct from

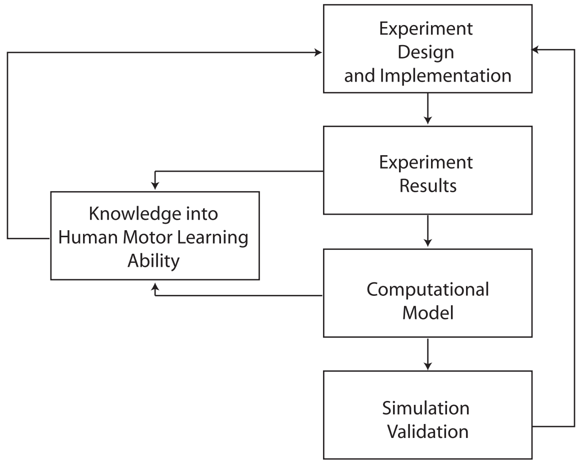

Figure 1. Overview of the procedure used to construct computational models of human motor learning.

the human motor system response, see also Franklin, Osu, Burdet, Kawato, and Milner (2003b) and Burdet, Osu, Franklin, Milner, and Kawato (2001). (The implied stationarity allows us to use more traditional ILC methods to start the development of human motor skill learning.)

Over the last two decades, many studies have been conducted to model human motor learning. This process follows the typical scientific method: formulate hypothesis, design the human motor experiments, and model or interpret the data to validate or reject the hypothesis. The process described here is a typical systems engineering top-down process, starting from behaviour to computational model and not one of building the human motor models from the cellular (neuron/muscle fibre) level upwards. (This bottom-up process is certainly a valid approach, but arguably much more complex, and for the present beyond verification.) It is summarised in Figure 1. Experiments are designed in which healthy human subjects are required to perform various, relatively simple tasks, such as grasping, drawing and reaching, within a robot controlled and measurement rich environment. The characteristics of the human motor learning behaviour (that is how the motor response evolves, which aspects of the human motor system are changed, and the rate at which these changes happen) are obtained from the observed experimental results. Next, these characteristics are extracted and used to construct a computational model to represent the human motor learning and human motor control ability. The computational model is then simulated and compared with the experiments to verify if the computational learning model can replicate, at least in a statistical sense, the human motor learning behaviour observed in the experiments. Both the experimental results and the computational models contribute to the knowledge of the human learning ability.

To illustrate the process, we present some of our own work in constructing computational models for two of the most cited human motor experiments in the literature (Burdet et al., 2001; Franklin et al., 2003b; Shadmehr & Mussa-Ivaldi, 1994). For more details we refer to Burdet et al. (2006), Zhou, Oetomo, Tan, Burdet, & Mareels (2012), Zhou et al. (2013), Zhou (2015) and Zhou, Oetomo, Tan, Mareels, and Burdet (2015).

An overview of the experimental set-up and protocols are presented in Section 3.1, followed by a summary of the construction of the computational model and some of the resulting simulation results in Section 3.2.

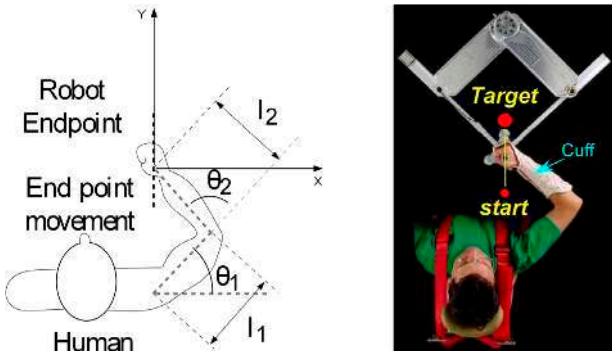

Figure 2. Setup of the experiment.

3.1. Experiment set-up and results

Refer to Figure 2. The figure illustrates healthy human subjects performing a point-to-point hand reaching task in a horizontal plane. The human subjects perform this reaching task while holding onto a robot, which is designed to exhibit negligible inertia and maintain the hand motion in the horizontal plane. Its sensors record the entire motion (of the hand) in detail, as well as the forces exerted by the hand on the robot.

The robot can also exert forces on the hand, so as to make the otherwise rather trivial reaching task an interesting object of learning, as the human subject has to overcome the robot exerted force in order to successfully complete the reaching task. By carefully designing the force fields exerted by the robot, it is possible to solicit various learning responses, and to elucidate the characteristics of human learning.

We refer to the case when no force is exerted by the robot as the null field. It represents the control experiment. It also serves the purpose of system identification of the subject's arm and characterising the typical or ideal motion executed by the subject.

When the disturbance force exerted by the robot depends only on the velocity of the hand, it is referred to as a velocity field (VF) experiment. When the disturbance force only depends on the position, it is referred to as a divergent field (DF) experiment. Both VF and DF are used to solicit learning responses.

In a VF experiment, the planar force disturbance $\mathbf{d}_i \in \mathbb{R}^2$ (where the index i is the number of times the task was repeated) is dependent on the subject's hand velocity $\dot{\mathbf{r}}_i \in \mathbb{R}^2$ (measured in the plane, by the robot sensors), here $\mathbf{r}_i \in \mathbb{R}^2$ is the position of the hand in the plane (also measured by the robot sensors). For example, a VF disturbance linearly dependent on the velocity is programmed as follows

$$\mathbf{d}_i = D_v \dot{\mathbf{r}}_i.$$

The tensor mapping velocity to force, D_v, is prescribed by the experimenter. It is independent of the iteration number, unknown to the subject, and is in fact the object that in some sense has to be *learnt* by the human subject.

In the divergent field (DF), the force disturbances $\mathbf{d}$ is dependent on the subject's hand position $\mathbf{r}$. A linear relation is represented as

$$\mathbf{d}_i = D_p \mathbf{r}_i,$$

where D_p is the tensor mapping position to force, as defined by the experimenter.

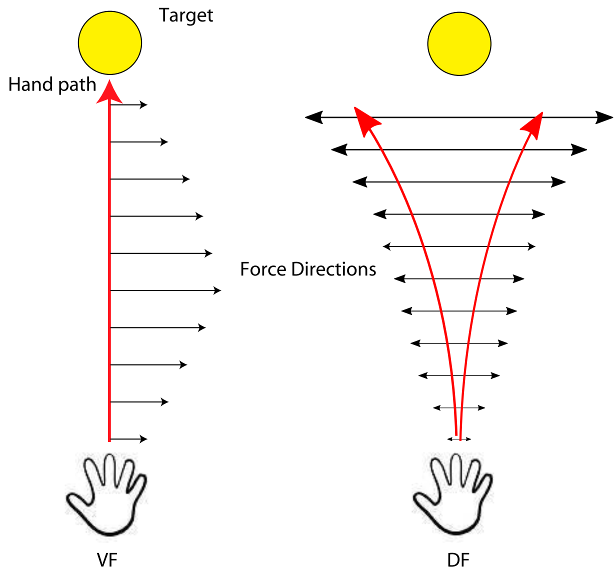

Figure 3. Disturbance forces applied to the hand when performing the task of point-to-point reaching.

Some very simple disturbance force fields, special cases of the above descriptors, applied to the subject's hand during the point-to-point reaching movement are shown in Figure 3. In the figure, $\mathbf{d}_i$ has only a non-zero component in the x-direction (orthogonal to the direction of motion), and this component only depends on the y-component (in the direction of the reaching task) of the hand's velocity or position (in case of a linear relationship, the magnitude of the force would be proportional to either the y-position or y-velocity, for the DF or VF, respectively).

The experimental protocol requires the human subject to first perform a prescribed number of motions under the null field. A trial is identified as successful when the subject reaches the end point with sufficient accuracy and precision. This initial phase allows the subjects to get used to the experimental conditions, and trains them to perform the task in a prescribed time interval. The successful trials in this phase are used to identify the natural human arm motion and verify the model. This start of the experiment is known as the *Initial Trials* phase.

After the *Initial Trials*, the artificial environment (whether in the form of VF or DF) is unexpectedly introduced to the subject. The subject is expected to learn and to overcome the disturbance field induced by the environment through trial and error by repeating the trials. This is the *Learning Trials* phase, which is often split in a before, early and late learning trial phase.

Once the subjects have learned to compensate for the disturbance field and are able to consistently perform the required task (with position and timing precision), the force field is unexpectedly turned off. The human's performance in trials in the subsequent null-field environment is recorded. This is the *After Effect* phase of the experiment.

The protocol for the entire experiment is illustrated in Figure 4.

Typical experimental results for both VF and DF environments are presented in Figures 6 and 7, respectively. From the experimental results, the following qualitative characteristics of human learning are observed:

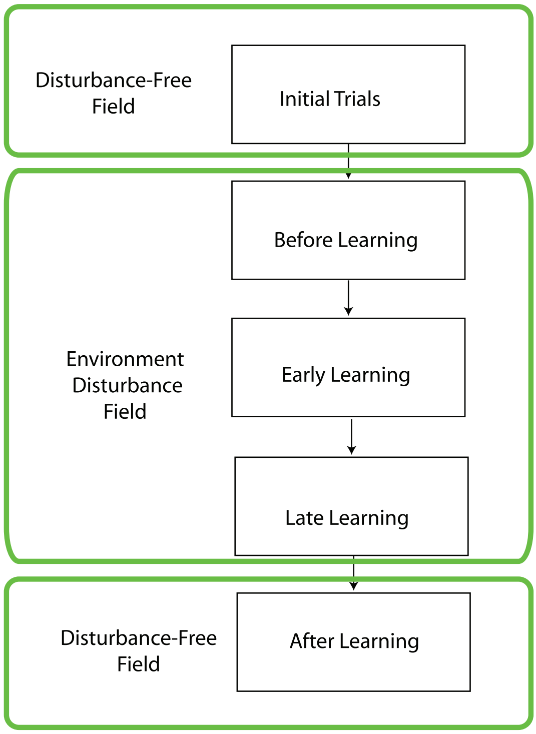

Figure 4. Protocol of the experiments.

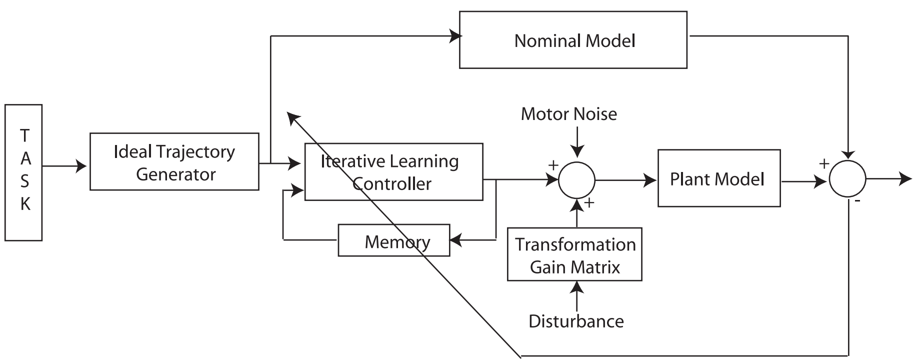

Figure 5. Computational models of human motor learning.

- Humans learn both the VF and the DF environment by observing the outcome of a trial per iteration, as opposed to learning over time during trials. That is the previous trials inform the behaviour in the next trial.
- For the VF environment, the motion in the After Effect phase is distinctly opposed to the Before Learning trajectories.
- For the DF environment, in the after effect the executed trajectories form a collection of straighter lines, and are in a tighter formation of lines, when compared to the collection of trajectories in the before learning phase.

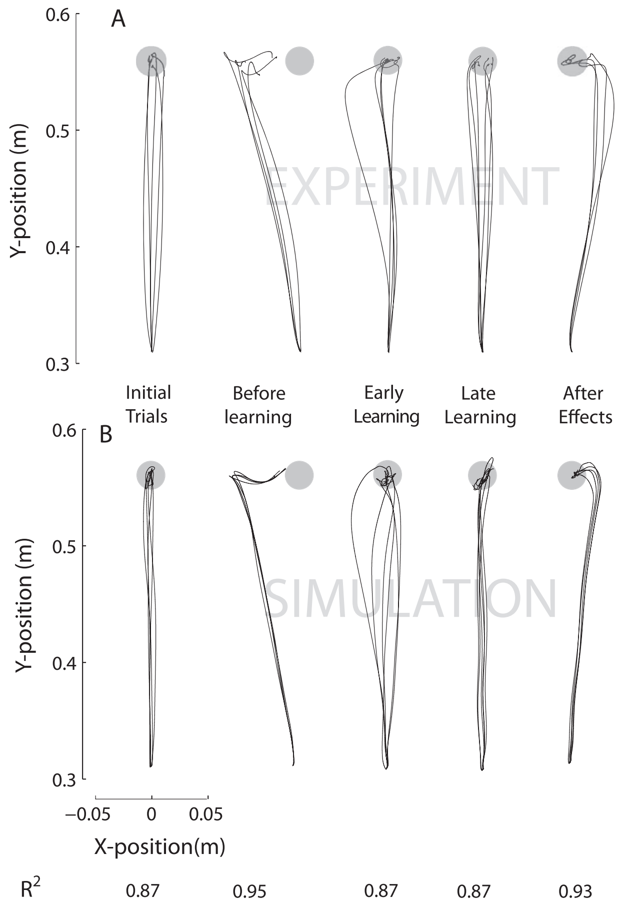

Figure 6. VF experiment and simulation results.

These qualitative observations are explained as follows.

- The VF disturbance is overcome by learning an internal model or representation of the external disturbance environment, much like in a feedforward control action.
- The DF disturbance is overcome by learning an (optimal) impedance matching (a different control) strategy Burdet et al. (2001), changing the arm dynamics through feedback and making the motion less sensitive to disturbances.

Clearly, humans use different control strategies depending on the (disturbance) environment. This motivates one to explore different experimental environments to gain a better understanding of the apparent complexity of the space of strategies explored in motor learning (Zhou et al., 2013). Much more work remains to be done in this space. Questions such as ‘How do humans select between strategies?’, or ‘How do we characterise the space of strategies?’ remain to be answered properly.

Remark 1 The experiments reported here consider learning in the context of external disturbances in the form of force fields, which is indeed a very common experimental set up (Burdet et al., 2006; Franklin, Burdet, Osu, Kawato, & Milner, 2003a, Franklin et al., 2003b, Franklin, So, Burdet, & Kawato, 2007; Osu, 2003; Shadmehr & Mussa-Ivaldi, 1994).

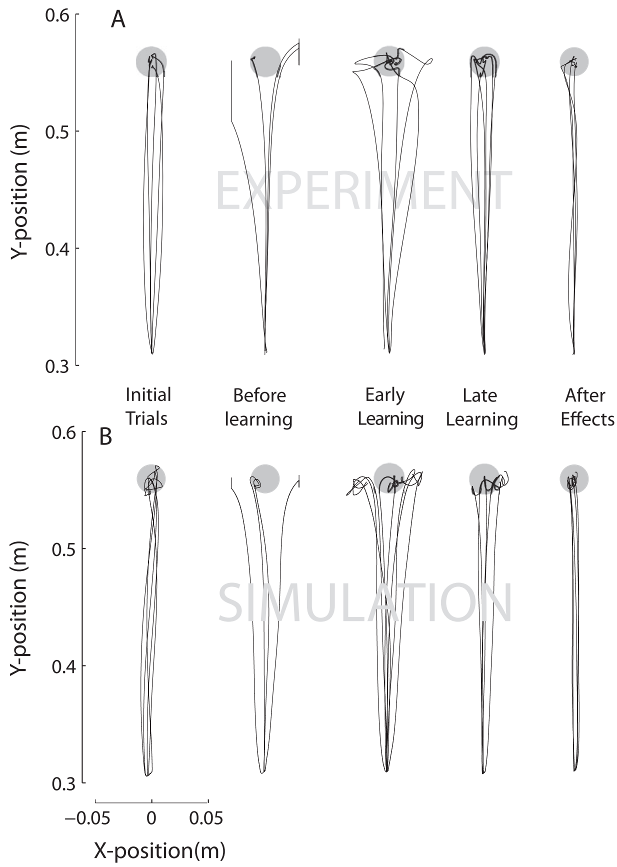

Figure 7. DF experiment and simulation results.

Other work, focuses on learning in the context of errors introduced in the subject's sensory feedback (mainly vision and proprioception) loops (Baraduc & Wolpert, 2002; Krakauer, 2005; Krakauer, Pine, Ghilardi, & Ghez, 2000; Shabbott & Sainburg, 2010).

3.2. Construction of computational models for healthy subjects

Experimental results, like the ones described above, provide rich data sets that can be used to design a computational model that is able to explain, and/or to simulate the observed experimental results.

The computational model is constructed using an ILC to execute learning, that is using the previous iteration's trajectory information to design the arm's behaviour in the next iteration. The design freedom, at each iteration, involves both a feedforward action, as in a reference trajectory, as well as feedback control parameters (used to change the impedance or 'transfer function' of the arm). An overview of this framework, based on Burdet et al. (2006) and Zhou et al. (2012), is presented next. It is illustrated in Figure 5.

To fix the ideas, a two rigid link manipulator model is used to approximate the motion of the human arm, with the hand as the end-effector on which the robot can exert a force (see Figure 2). The associated dynamic equations are of the form

$$M(\mathbf{q}_i)\ddot{\mathbf{q}}_i + C(\mathbf{q}_i, \dot{\mathbf{q}}_i)\dot{\mathbf{q}}_i + G(\mathbf{q}_i) = \boldsymbol{\tau}_i + J(\mathbf{q}_i)'\mathbf{d}_i.$$

The index i refers to the iteration number, and q is the generalised coordinates vector, a vector of joint angles and τ is the associated vector of joint torques. As before $\mathbf{d}$ is the disturbance force field generated by the robot arm acting on the hand. The functions M, C, G, and J represent the inertia, coriolis forces, gravity effect and the end effector (hand) Jacobian, respectively. The inertia is assumed to be non-singular throughout the entire work space.

These non-linear dynamics can be feedback linearised by defining the joint torques in the obvious manner as follows

$$C(\mathbf{q}_i, \dot{\mathbf{q}}_i)\dot{\mathbf{q}}_i + G(\mathbf{q}_i) + M(\mathbf{q}_i)\mathbf{u}_i = \boldsymbol{\tau}_i,$$

where we introduce a new input through $\mathbf{u}$. Using these definitions, the arm movement is thus governed by

$$\ddot{\mathbf{q}}_i = \mathbf{u}_i + M(\mathbf{q}_i)^{-1}J(\mathbf{q}_i)'\mathbf{d}_i$$
$$t \in [0, T_i],\ \mathbf{q}_i(0) = \mathbf{q}_0,\ \dot{\mathbf{q}}(0) = \mathbf{0}$$

where $\mathbf{u}_i(t) \in \mathbb{R}^2$ are the motor (joint torque) commands (after feedback linearisation); $\mathbf{d}_i(t)$ is the disturbance force imposed via the robot in the ith trial; and $\mathbf{q}_0$ is the fixed initial condition, which is the same at each iteration i. The latter condition is enforced by the robot platform (and the experimental protocol), which returns the hand to the start position before the next trial commences. The ith trial last T_i time units, and the trial is a successful one provided the final hand position is sufficiently accurately placed, with appropriate timing $\|T_i - T_d\| \leq \eta$, where $\eta > 0$ is a small tolerance, representing timing error.

To define the actual control action to be learnt, a reference model, that defines the desired controlled system behaviour, is used. In the present context, the reference model is learned from the data in the *Initial Phase* using system identification methods such as least squares (Ljung, 1998; Spong, Hutchinson, & Vidyasagar, 2006). It is assumed that the behaviour in this initial phase, without any perturbations is the natural behaviour that the human would prefer to execute. Given the measurements from the *Initial Phase*, a reference model of the form

$$\ddot{\mathbf{q}}_r = \mathbf{u_r} \tag{1}$$

or equivalently

$$M(\mathbf{q}_r)\ddot{\mathbf{q}}_r + C(\mathbf{q}_r, \dot{\mathbf{q}}_r)\dot{\mathbf{q}}_r + G(\mathbf{q}_{r,i}) = \boldsymbol{\tau}_r.$$

(completed with the appropriate initial condition, and defined over $t \in [0, T_d]$ is used to represent the ideal (or equilibrium) trajectory which is planned by the human subject during each iteration. It is essentially the mean trajectory over all the (accepted) trajectories in the initial phase. This reference trajectory captures the effect of the implicit visual and other motor sensory feedback loops active in the task execution through the so-called reference input τ_r or $\mathbf{u_r}$.

The motor commands $\mathbf{u}_i(t)$ is modelled as a controller of the form:

$$\mathbf{u}_i(t) = \mathbf{u}_r(t) - K_{1,i}\tilde{\mathbf{q}}_i - K_{2,i}\dot{\tilde{\mathbf{q}}}_i + K_{3i}(t), \quad t \in [0, T]. \tag{2}$$

Here $\tilde{\mathbf{q}} = \mathbf{q}_i - \mathbf{q}_r$, and $\dot{\tilde{\mathbf{q}}} = \dot{\mathbf{q}}_i - \dot{\mathbf{q}}_r$, while $K_{1,i}$ and $K_{2,i}$ are matrix gains to provide a stable second-order response from the disturbance to the hand position, with a reasonable bandwidth (allowing the disturbances to be measured). These can be fixed independent of the iteration, or updated at each iteration to adjust the bandwidth of the closed loop arm model, depending to what extent one chooses to reject the disturbance by feedback action or feedforward action. This can be settled using a criterion to minimise the overall control action. Assuming that the $K_{1,i}$ and $K_{2,i}$ are fixed, the estimate for the disturbance $K_{3,i}$ (the feedforward action) may be updated using a simple ILC iteration as follows:

$$K_{3,i+1}(t) = K_{3,i}(t) - \beta \mathbf{e}_i(t), \qquad t \in [0, T] \tag{3}$$

where $\mathbf{e}_i = \mathbf{q}_r - \mathbf{q}_i$ is the joint angle error, and $\beta > 0$ (and small) is the update gain of learning controller. This update law has been shown to be convergent across iterations, enabling the model to simulate human motor learning behaviour when presented with the external disturbances. The rate of learning β is selected so as to mimic the human rate of learning over the iterations. For the above learning to identify the disturbance well, it is necessary that the spectrum of $\mathbf{d}$ is well inside the bandwidth of the controlled system $(s^2 I_2 + K_2 s + K_1)^{-1} 1_{2\times 1}$. (If not the disturbance, or a spectral part of it, will be significantly attenuated by the feedback controller itself. This indicates a level of ambiguity, and non-uniqueness of appropriate control which is a function of the selection of the $K_{j,i}$'s ($j = 1, 2, 3$) and β as well as $\mathbf{d}_i$; even in this simple learning environment!)

Alternative control models may be conceived, for example, all control gains, feed-forward action and feedback action could be subject to learning. Despite the inherent complexity, such designs will perform adequately when well tuned. Indeed, the simulations presented here in Figures 6 and 7 are based on a design that subjects all gains to learning, starting from a zero initial condition for these gains.

In Figures 6 and 7, we compare the simulation outcomes with the experimental results for the VF and DF environments, respectively. Clearly, the constructed model is able to capture the experiment results and from this we infer that the human motor learning ability is adequately captured through the ILC. As this structure is rather flexible, it can be readily deployed in the rehabilitation context.

Remark 2 In Figures 6 and 7 , trajectories generated using the model are compared to those recorded from experiments to demonstrate the ability of the framework to capture the qualitative characteristics of human learning in the two dynamic fields. However, if the model is to be used to verify a hypothesis about a certain characteristic of human motor learning, then the simulation and experimental results are generally compared quantitatively using factors such as learning rates (Zhou et al., 2013), stiffness geometry (Burdet et al., 2000), endpoint force (Burdet et al., 2001), endpoint position (Zhou et al., 2013), velocity profile (Flash & Hogan, 1985; Zhou et al., 2012) and accuracy in reaching the target (Fitts, 1954; Qian, Jiang, Jiang, & Mazzoni, 2013). For instance, learning rates have been compared using the model in order to show that different subjects learn at different speeds in the two different fields, demonstrating the need for a subject-specific models to fully capture an individual's learning capacity (Zhou, Oetomo, Tan, Burdet, & Mareels, 2012; Zhou et al., 2013).

Remark 3 There is no compelling reason to believe why the ILC model developed here is in some sense the unique, or indeed 'the' preferred model. (As indicated there is significant design freedom in the selection of feedforward and feedback design as well as how the learning is conceived.) What the experiments have shown us, is that our hypothesis of an ILC acting on a reference trajectory and an impedance matching controller, cannot be rejected, that is, the computational model is compatible with the experiments.

Remark 4 Nevertheless the model has promise, as it is able to work across a variety of learning environments, and because it enjoys strong robustness properties, as demonstrated in the ILC literature, it indeed deserves further evaluation. For example, it is possible to incorporate signal dependent noise and uncertainties into the model using stochastic ILC (Saab, 2003), enabling it to model experiments which investigate human learning with different environment noise and uncertainties (Kording & Wolpert, 2006; van Beers, 2009; Wolpert & Landy, 2012). Furthermore, our recent experiments have also shown that the model remains valid even in the context of sensory disturbances, in addition to dynamic disturbances. In particular, the model captures point-to-point learning control in the presence of erroneous visual feedback (Zhou et al., 2013).

Remark 5 There are many other, and quite different, models in the computation human motor control literature that focus on learning. Some are based on Kalman Filters (Battaglia & Schrater, 2007; Berniker & Kording, 2008; Ernst & Banks, 2002; Kording & Wolpert, 2004, 2006; van Beers, 2009, 2012), and machine learning (Peters & Schaal, 2008; Shteingart & Loewenstein, 2014), or learning a class of parametrised motor primitives (Mussa-Ivaldi & Bizzi, 2000; Nori & Frezza, 2005) and even optimal control design (Li & Todorov, 2004; Todorov, 2004; Todorov & Li, 2005). Many reviews of these models have been conducted, see for example (Haith & Krakauer, 2013; Schaal & Schweighofer, 2005) and references therein for more details. Surprisingly all these methods are based on open loop methods, as they focus the entire learning on the design of the feedforward trajectory. It follows that these methods lack in robustness with respect to uncertainties in the arm model, e.g. fatigue effects cannot be catered for, and indeed external disturbances (Zhou & Doyle, 1998). In addition, many of these techniques such as as reinforcement learning ones (see for example, Doya, 2000; Peters & Schaal, 2008) rely on appropriate data to update its model and cost function through a reward-based method. With sufficient data, it can learn a static mapping or dynamic model using some optimisation schemes to match the data. Usually the model structure is fixed and it is thus hard to show its robustness to modelling errors. Moreover it is hard to adapt the changing environments. It is therefore not an ideal tool to apply RL for human learning as during human learning, the environment is always changing or even changes unexpectedly. ILC, on the other hand, is model-free method.

It does not require a precise knowledge of the model, thus it is more robust to modelling uncertainties. Moreover, ILC has been shown to less sensitive to changing environments (Moore et al., 1993; Xu & Tan, 2003). These two features can be observed in human learning (Zhou et al., 2013).

Thus ILC is more suitable to model human learning. Our computational model has also demonstrated that ILC can work even when the human's identified model is different from the computational model throughout the learning process. (See also Section 4.)

4. Towards improving rehabilitation

With the definition of these models for motor movement and learning, the question is asked, how do these affect our decision making in the design, construction and programming of future generations of rehabilitation robots? In this section, we pose a number of open questions and areas of future investigation. Particularly, in Sections 4.1 and 4.2, we discuss the possibility that existing models of learning may need to be adapted to model recovery, and we offer some initial ideas on how to do this. In Section 4.3, we discuss how an appropriate model of recovery may change how we view neuro-rehabilitation.

4.1. A model of recovery?

The underlying assumption within the application of human motor learning models to rehabilitation is that the motor learning process is equivalent – or similar – to the motor recovery process. This leads to the obvious question, 'Is this assumption valid?'.

Our current understanding and modelling of the recovery process is limited by a lack of studies on the modelling of this recovery, which, in part, is due to the large variability in the presenting symptoms of these patients. Recruitment of appropriate patients for modelling is a difficult process, as the recovery characteristics of each patient have to vary significantly depending on their presenting symptoms. Thus, any attempt to validate a model presents some difficulties. At present, research into human motor learning is leveraged, based on the similarities in being presented with an unfamiliar environment (for example, that of dynamic or visual disturbances), and a motor impairment (when the dynamics of the human motor system are disturbed). However, it is also obvious that these situations are not entirely equivalent. Clearly disturbances in the motor learning experiments are external and are generated at the environment level, whereas the disturbances experienced by an impaired patient are internal and may include impairment at the actuation level. It is therefore unlikely that learning and recovery are indeed equivalent.

To capture recovery properly the identification of a mobility model for each patient is essential. That is the learning controller has to establish the starting point and then slowly explore a transition to a rehabilitation condition. Learning controllers, such as ILC or the windsurfer controller are capable of doing this in principle, but a clinical evaluation of such approaches has not been completed to date. As observed above, the end condition will most likely depend on the explorative trials, and as such, the design of the entire rehabilitation process is highly non-trivial and will have to incorporate the learning from physiotherapy in order to achieve acceptable clinical outcomes, and guarantee widespread adoption.

4.2. Optimal and target trajectories

In modelling motor movement, it is commonly accepted that the human motor system performs optimisation (Guigon, Baraduc, & Desmurget, 2007; Kang, He, & Tillery, 2005; Nakano et al., 1999; Sekimoto & Arimoto, 2005; Tahara, Luo, & Arimoto, 2006; Todorov & Jordan, 2002; Uno, Kawato, & Suzuki, 1989) – that is, the human motor system internally resolves the inherent redundancy in any reaching movement by minimising a particular cost function, including those related to energy (Franklin et al., 2007), a static goal (Fitts, 1954) or variance (Todorov & Jordan, 2002). This optimised trajectory is termed the 'nominal' or 'ideal' trajectory. Above, in motor skill learning with healthy subjects, this ideal trajectory is often found through the null field experiment – measured in the absence of disturbances to the system – and the learning process is modelled towards relearning this optimal trajectory, as discussed in Section 3. However, in patients with impairment, the ideal trajectory is difficult to define. The dynamics of the patient's system may have changed, and the injury may now make activation of certain muscles more costly or difficult. Indeed, the pre-impairment ideal trajectory in joint or task space may no longer be feasible, let alone optimal.

In general, after impairment the patient learns towards a new, unknown, optimal trajectory. That is, the patient recovers towards some new optimal, and unknown trajectory, within the realm of feasible trajectories. When observing patients that compensate for their disabilities, they often make what appear unnatural movements, such as large movements of the trunk and shoulder to compensate for difficulties in extending the elbow during reaching actions. This is being explored in a relatively new model of learning (Jiang & Jiang, 2014a, 2014b), where the learning incorporates the learning of the desired trajectory.

This discussion parallels a discussion between therapists. Some therapists define the goal of therapy as retraining to be able to complete the task, regardless of the trajectory being perceived as normal or not. Others, however, attempt to shape the movement from the beginning of the rehabilitation, in an attempt to recover as much of the normal (pre-impairment) trajectory as possible. Clearly, both approaches have their place, and the appropriate path depends on the patient's condition (Michaelsen, Luta, Roby-Brami, & Levin, 2001).

4.3. Rehabilitation modalities and body augmentation

A complete model of learning and the recovery process would provide indications of what to change to encourage the best possible outcome in rehabilitation, or indeed if rehabilitation should involve an augmentation of the body through an exoskeleton, and/or muscle stimulation device. In any situation, the rehabilitation trajectory must be patient specific, and should explore the appropriateness of all options within the context as presented. The design of the robotic devices themselves will gain much from these models of learning.

Exoskeletons are often considered for their ability to modify the positions of all joints of the arm, rather than just the end effector (or hand). However, does the significant additional expense involved in constructing a fully actuated exoskeleton over a manipulandum lead to significant improvement of the rehabilitation process? Can comparable rehabilitation outcomes be achieved using robots with some or all joints passively actuated? Can a simpler mechanism be used with some auxiliary inputs, such as proposed in Crocher, Fong, Klaic, Oetomo, and Tan (2014) and Thielman (2010)? Alternatively, do we require actuation at a muscle level, using functional electronic stimulation (FES) in conjunction with robotic devices? The coordination and control of such inputs can also be developed using the above ILC framework (Freeman et al., 2012).

5. Conclusions

The potential of robotics in the field of motor skill rehabilitation is significant. The present state of the art in robotic rehabilitation struggles with capturing in patient specific manner the initial capability as well as charting an acceptable course to an acceptable rehabilitation end goal. Certainly for the immediate future, motor skill recovery therapy will depend, as it does now, on the skill of a well-trained therapist guiding the entire rehabilitation process.

The greatest immediate promise stems from the superior quantitative information available from robot-assisted rehabilitation. Building on this information, the steps to highly automated rehabilitation robotics require

- a clinically accepted protocol to identify and to quantify, the mobility condition at the onset of rehabilitation (which is difficult to measure and capture through experiments precisely due to the limited motor ability, and the large variety of possible conditions)
- a clinically accepted protocol to explore mobility improvements (realising that the end condition will depend on both the robotic assistance, and the sequence of trials followed in the rehabilitation process)
- a clinically accepted protocol to characterise an accepted final rehabilitation condition.

Much work remains to be done. Nevertheless, it is our contention that classical learning control algorithm show great promise. Progress will require substantial partnerships between specialists in robotics, learning (control) and rehabilitation therapy. Through such partnership much will be understood about learning, which in turn will assist the development of more natural human–robot interfaces, where robots 'learn' how to interact depending on the circumstances.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work is supported by the Australian Research Council (ARC) under the Discovery Project [grant number DP130100849] and the ARC Future Fellowship [grant number FT0991385].

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