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SPECIAL ISSUE - REVIEW

Assessing the effectiveness of robot facilitated neurorehabilitation for relearning motor skills following a stroke

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Abstract A growing awareness of the potential for machine-mediated neurorehabilitation has led to several novel concepts for delivering these therapies. To get from laboratory demonstrators and prototypes to the point where the concepts can be used by clinicians in practice still requires significant additional effort, not least in the requirement to assess and measure the impact of any proposed solution. To be widely accepted a study is required to use validated clinical measures but these tend to be subjective, costly to administer and may be insensitive to the effect of the treatment. Although this situation will not change, there is good reason to consider both clinical and mechanical assessments of recovery. This article outlines the problems in measuring the impact of an intervention and explores the concept of providing more mechanical assessment techniques and ultimately the possibility of combining the assessment process with aspects of the intervention.

Keywords Outcome assessment · Rehabilitation · Robotics · Stroke · Machine mediated neurorehabilitation · Mechanical impedance

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1 Introduction

Strokes, transient ischemic attacks and traumatic brain injuries are conditions that are all related in that there is vascular damage that ultimately causes neuronal death in the brain. Trends in the management of stroke as an emergency condition have resulted in a better survivability, but strokes still remain as the leading cause of disability in the developed world [19, 35]. There is strong evidence that early, intense and challenging neurorehabilitation programmes have a significant effect on the functional outcome following a stroke [37], but the cost of administering these treatments tends to be high. The full cost of the stroke should consider the treatment cost combined with the ongoing costs of caring for a person following a hospital discharge; however, very few economic models consider this link and the pressure remains to simply reduce the treatment cost.

Intelligent machines and robotic systems may provide a good method for reducing the hospitalisation costs as well as providing new ways of delivering retraining therapies, whilst monitoring and assessing recovery. A reduction in cost may be possible by the simple expedient of ensuring that neurorehabilitation therapists focus on specifying and monitoring progress, and allowing machines to deliver specific therapies to the individual [14, 29, 39]. It is probable that the reduced staff cost will outweigh the equipment costs but this will only be accepted if there is no negative effect on patients. An additional justification for introducing machine facilitation of therapies is the potential to replace aspects of treatment that are difficult, dangerous or repetitive for the therapist. For example, if machines provide partial body weight support in gait retraining, then additional therapists are not needed to guard the person against a fall. Likewise relearning gait often requires a therapist to do the difficult and repetitive task of moving the patient's foot in a specific pattern during walking, a task that may be more readily handled by a machine. These two functions are available in lower limb retraining machines such as the Lokomat,[1] although further research is still needed to add higher levels of sensing and intelligence into the control systems to allow monitoring and adaptations to the patient whilst giving the therapist a high level of confidence that the machine will respond in a clinically appropriate way. A third advantage of machine supported neurorehabilitation is that there may be therapy or assessment actions that can only be achieved by fast and sensate machines. Continuous quantitative monitoring, adaptive control and the ability to impose large and short perturbing forces onto the limb as a way of measuring impedance are all examples.

Because of a growing pressure to reduce hospitalisation costs it is reasonable to surmise that increasingly rehabilitation will move away from the hospital to specialised units, the home and local medical health facilities. A possible scenario is demonstrated in Fig. 1 where the individual is treated at multiple sites, depending on their level of health and needs. Thus, although treatment might begin in a specialised unit in a general hospital, the long-term rehabilitation needs are best met in a specialised rehabilitation unit, or (if the person is responding well) as an outpatient in a local hospital. This model is compatible with the concept of early supported discharge where, if sufficient care is available in the community, the patient can be discharged early from the stroke unit thus realising a direct financial gain for the healthcare funder [40]. New methods of providing machine based interventions for stroke treatment need to accommodate this trend by increasing the levels of customisation of the treatment, and by allowing the treatment to move seamlessly with the patient through the health system. This can be combined with the recognition that machine delivered therapies can provide motivating and challenging therapies, and improve the socialisation of the individual and their carers throughout the recovery process [14, 26]. Not only must the technologies that provide therapies be designed to accommodate this trend, but also new high quality assessment techniques are needed that can monitor the impact of treatments.

This article considers assessment techniques for advanced machine interventions that include robotics, and is structured as follows: first the manuscript investigates the traditional clinical evaluation of stroke treatment and considers new techniques for assessment of clinical effect. It then goes on to identify possible new methods that could be sensitive to parameters relevant to stroke recovery, that is measures of

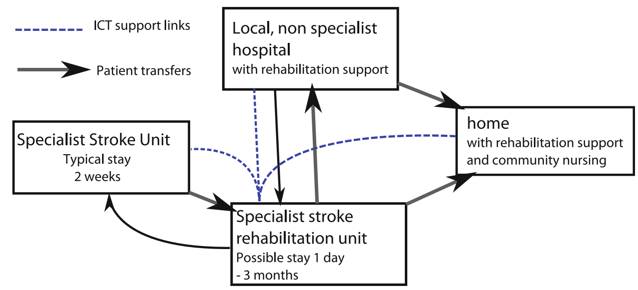

Fig. 1 In the future stroke recovery management will probably require managing patient transitions between different recovery facilities while providing uninterrupted information and communication (ICT) support

recovery attributes at the muscular-skeletal level, the primary reflexes, and central nervous system. These methods rely on observing the imposed forces and velocities on the individual. These observations can be correlated to externally imposed forces, torques, position perturbations, etc. A framework is established to allow separation of measures at sub-levels (muscular-skeletal recovery, recovery of reflex loops, motor patterns and short term skills). The article makes a further observation of the methods needed in addition to mechanical methods (in particular MRI and fMRI based) to evaluate the abilities of a person to embed skills. Ultimately, it is the combination of the classical clinical measures, the mechanical measures and measures based on brain imaging that will give the most complete picture of the recovery process. Ultimately more precise knowledge will allow therapies to be chosen that favour the best output for each individual in this highly varying condition.

2 Challenges of assessing robots in neurorehabilitation

Most evaluations of robotic aided interventions in stroke rehabilitation have tended to consider only a single intervention group. It is thus difficult to distinguish between the effects of the robot intervention, any other rehabilitation treatments and any spontaneous recovery. The reason this occurs is that often there is a high level of effort invested in the engineering of the device, and with a consequent difficulty of producing sufficient systems for a reasonably large study to take place. The cost of production of rehabilitation devices is significantly higher than the cost of producing drug treatments so even if a controlled trial occurs, the level of exposure and intensity is limited when compared to a drug trial.

There are broadly two intervention methods that can be practically considered in robot-assisted neurorehabilitation. The first is to control the subject against themselves, that is to submit half the subjects to a condition where they receive robot treatment, along with any other treatments, in

[1] Hocoma, Switzerland.

the first phase followed by a second phase where only the other treatments continue. The second group has this order reversed. There are any number of variations on this model, such as including measurements during a baseline and a washout period.

The second controlled intervention is the classic randomised control trial (RCT) where subjects are divided into a treatment and a control group, often matched for parameters such as age or severity of stroke. This is a widely accepted method for evaluating the impact of a treatment but in the case of robots for neurorehabilitation, and is very costly to evaluate.

Both interventions suffer from the fact that the trial subjects cannot be blinded to the intervention, that is to say they are likely to know if they are receiving robot-assisted treatments [10].

A recent multi-centred RCT study of one particular robot intervention (MIT-manus) considered three comparison groups, one receiving robot intervention (repetitive proximal and distal arm therapies), one receiving intensive comparison physiotherapies and the third receiving the usual care [23]. The study provided 36 sessions of treatment over 12 weeks for subjects who were at least 6 months after their original stroke. The conclusion was that for this particular treatment, the robot intervention was comparable with the intensive therapy and outperformed usual care. Cramer [6], in the editorial for this journal issue, observed that there were several unusual factors, such as the high levels of depression in the subjects. In addition, since this was a Veterans Affairs (VAs) sponsored study, the reported results reflect recruitment of subjects from within the VA hospital system rather than the general stroke population. Cramer observes robot therapies have great potential and can provide therapy modes not explored by this study. Kwakkel et al. [21] review a number of RCT studies in robot-assisted therapies on the upper limb with inconclusive results, and argue for better measures to discriminate between recovery of functional abilities (where compensation techniques such as trunk movement might be used) and the genuine recovery of motor skills.

Whilst the randomised control trial is considered the gold standard for the evaluation of new treatment interventions, the model presents a number of challenges for the evaluation of novel interventions in stroke, for a number of reasons.

1. The complexity of the brain and nervous system means that it is impossible to identify 'similar' strokes. People who have had a stroke present with multiple problems due to these damaged structures. The impairment of function varies depending on the size, location and nature of the cerebrovascular insult [16], and is compounded by allied problems ranging from speech impairment to emotional and psychological difficulties. Hence the formation of a homogeneous sample is substantially hindered.
2. A well-controlled RCT should ideally have a well defined treatment, for example, a drug dosage that can be related to age, gender, weight etc. The variability of each individual's post-stroke presentation will inform the type and amount of exercise intervention that is both appropriate and acceptable to the person with stroke. If the intervention is too prescriptive, it runs the risk of being incomprehensible, ineffective or insufficiently stimulating or engaging for the person with stroke.
3. Re-learning motor skills after stroke requires repetition of task-oriented, functional movements. The level of repetition reached in routine intervention is likely to be insufficient to optimise recovery and rehabilitation, and additional therapy has been shown to be limited unless it is in the region of 900–1200 min, i.e. approximately 30 min daily for up to 6 weeks. Compliance with augmented therapy programmes has traditionally been low [9].
4. In general, it is not possible to blind the person with stroke from the intervention hence the best that is achievable is a randomised controlled trial where the person doing the assessment measures is blinded to the intervention but the subject is not.
5. A wide choice of clinical measures is available (examples used in some studies on the impact of robots in neurorehabilitation are given in Table 1) and must be selected for sensitivity, ease of use, floor and ceiling effects etc.

Table 1 A subset of available clinical scales for assessment of parameters relevant to stroke recovery

Scale		Time to administer (mins)
Tardieu scale	S	
Modified Ashworth scale	S	
Orpington prognostic score	ss	5
Stroke impact scale	ss	15–20
Barthel index	A	2–20
Functional independence measure	A	30–45
Fugl-Meyer motor scale	F	20
Action Research arm test	F	7–10
Chedoke-McMaster stroke assessment scale	F	45–60
Motor assessment scale	F	15–60
Rivermead motor assessment	F	45
Wolf motor function test	F	30

ss stroke specific, *S* spasticity, *F* function, *A* activities of daily living

6. Given the complexities and differences between and within health services and systems, multi-centred trials for rehabilitation interventions prove difficult at the level of the control of the intervention and the measurement of various outcome variables. Hence the recruitment of sample sizes that are sufficiently large is a challenge.

Recent experience by one of the authors (ES) has demonstrated that a mixed method approach yields rewarding, robust and relevant information for the evaluation of novel ways of mediating exercise intervention after stroke [9, 10, 11]. Using the Medical Research Council's framework for the development of RCTs in the evaluation of complex interventions, Galvin et al. used a variety of quantitative and qualitative research methods to design and evaluate 'family mediated exercise intervention after stroke' (FAME). In a pre-clinical or theoretical phase, a systematic review and meta-analysis was completed to understand the research evidence about augmented exercise interventions after stroke with a particular emphasis on which participants were best suited, what dose was required and what compliance issues emerged. In the second phase (modelling phase), semi-structured interviews and focus groups were carried out with the 100 family members/friends of people with stroke, 75 people with stroke and 10 expert physiotherapists. The combination of these studies resulted in the design of a patient centred, evidence-based intervention that was informed by the beneficiaries, that is people with stroke and their families. The final phase was a multi-centred, controlled trial where the person taking the measures was blinded to the intervention, and followed the design shown in Fig.2, with 20 subjects in each arm. Clinical measures were made at baseline, 8 weeks and 3 months, the latter to determine if the effects of the intervention were persistent. The intervention consisted of 1200 min of exposure to the treatment over the 8-week period, and with this level of intensity the study was able to show a positive effect in the chosen clinical measures.

The RCT was combined with a nested qualitative analysis with in-depth semi-structured interviews carried out with the participants with stroke and the family members. The quantitative output of the RCT demonstrated clinical effectiveness however the output from the qualitative research revealed an impact that would not be captured by simply using clinical outcome measures [11].

3 Machine-based measures

A principal advantage of machine-based measures of stroke recovery is that they are objective. The challenge is

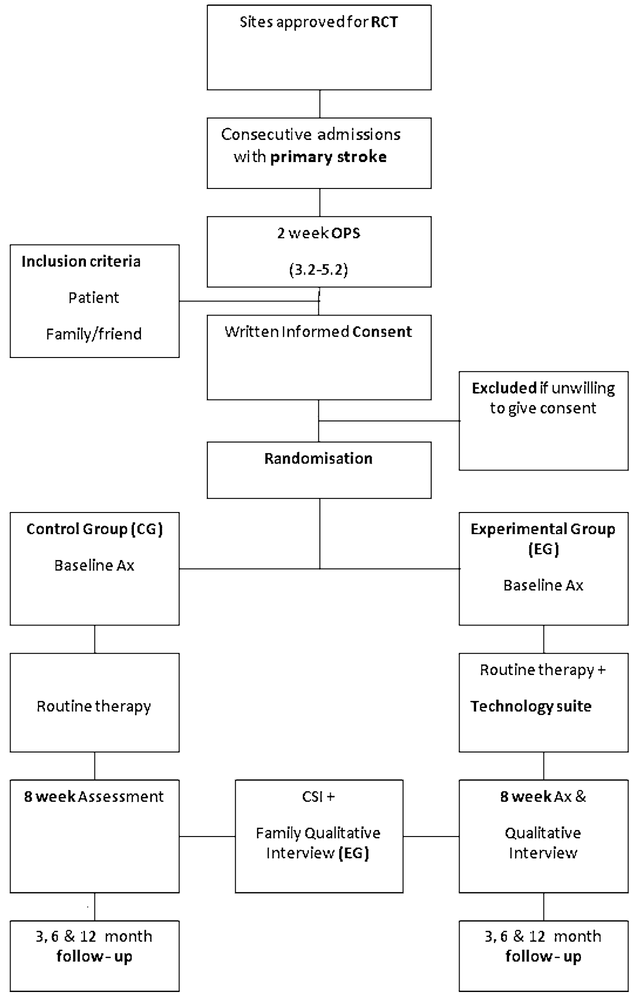

Fig. 2 Flow diagram used in the FAME project [43]

to identify a set of measures that are able to give information about the recovery state that has high specificity and low noise. Practical considerations include the time a test takes to be set up and administered as well as the disruption it may cause. The intervention therapies considered are directed to retraining the motor skills associated with upper and lower limb movements so the measures will be considered in this context.

This article considers assessing recovery of intentional movements in four ways that loosely correlate to the levels of recovered skill, that is

- Monitoring force and position parameters during the execution of a predefined task
- Imposing a short duration force or position perturbation either in isolation or during a task
- Imposing a learnable force perturbation
- Assessing long-term skill learning

To succeed as a clinical measure any mechanical measurement method must (a) demonstrate clinical validity,

(b) be easy to administer and (c) reflect the true underlying biomechanical and neural systems [17]. If the test is sufficiently well considered, there is potential to distinguish the mechanical parameters of the joint, and use these to distinguish between the pure mechanical response, the reflex mediated response and higher centres of the brain.

3.1 Monitoring force and position during a task

When considering a person performing an action such as inserting a key into a lock the parameters can be considered in several ways. The forces and torques on the key due to the hand and the lock can be considered. The same action is the result of the combinations of torques and forces on the joint from the muscles and the forces transmitted from the world through the bones and other tissues. In the same way forces and torques can be considered at the endpoint (key) or joint space, the velocities, positions and accelerations of individual muscles, must relate to those at the joints, and the end point. Knowledge of any space such as the joint can help to determine the state in another space such as the end point. These relationships allow knowledge of parameters in one space (such as that of the key) to inform us of parameters in another space (such as the joint) [33]. This discussion assumes a set of forces are applied to a kinematic linkage (that is the bones within the skeletal frame) from both internal (muscles) and external sources, resulting in movement of that linkage. A useful simplification is often made when considering arm movement, the elbow and shoulder can be modelled as a simple pin and a simple spherical joint, respectively. Further simplifications might then restrict movements to a plane further reducing the unknown variables describing the movements of the person allowing a simple relationship to be expressed between the different spaces (muscle and joint endpoint).

Any machine using feedback control requires measurements from a set of sensors. Information from these sensors allows an estimate of the forces and velocities of the machine at the point(s) of contact with the person. There may be a potential to process this information to give a metric for the performance of the person. This concept was used by Mak et al. [27] to get measures of 'work' or energy expended or absorbed by the individual using the Gentle/s rehabilitation robot [24, 25] although the idea can be applied more generally.

The method described above was used to estimate the mechanical work done by the elbow and shoulder joints during reaching movements whilst the person was using the Gentle/s robot. A number of modes were available on Gentle/s, all imposing forces via a wrist-hand orthosis onto the individual [1]. These external forces were designed to assist intentional movements towards a goal and could be imposed for all or part of the individual's movement. The haptic device was admittance controlled, and therefore transmitted forces via a 3 axis force sensor that could deliver an estimate of the endpoint force in Cartesian space, $\mathbf{f}$, to the logging software. This was coupled with the intrinsic joint sensors on the haptic device as well as a set of passive measurement sensors to give a fully resolved position and orientation state of the point on the wrist where the forces were applied, $\mathbf{x}$. An additional measurement of the flexion angle of the elbow, α, was needed to fully resolve the estimated joint parameters, θ.

The arm was modelled as a two-link serial chain with five degrees of freedom. The vector of joint angles, θ, consisted of three shoulder angles and two elbow angles. An inverse kinematic model was then generated to give an estimate of the five joint angles. That is

$$\theta = f(\mathbf{x}, \alpha)$$

The internal joint torques can be estimated from the arm Jacobian—now computable from θ. External forces in this case consisted of the forces applied by the wrist attachment to the haptic device, $\mathbf{f}$, a vector of gravity terms, $\mathbf{g}$, and a vector of the external wire supports used to compensate the arm against gravity, $\mathbf{w}$. From this combined force vector and the computed Jacobian the internal joint torque, τ, is estimated as

$$\tau = J^{\mathrm{T}} \begin{bmatrix} \mathbf{f} \\ \mathbf{g} \\ \mathbf{w} \end{bmatrix} \tag{1}$$

τ must represent the combination of muscle forces, passive tissues, joint friction forces and torques, etc. associated with movement. The results for a single individual using a mode (mode 1) where the haptic device could provide all external energy are shown in Fig. 3. Clockwise arrow directions indicate that the person is doing work on the haptic device whereas counter-clockwise directions indicate the joint is absorbing energy. Thus, in this example, it is readily seen that the person is expending energy through elbow flexion but is absorbing energy in all three degrees of freedom associated with the shoulder. The area contained within the curve is then a measure of energy expended or absorbed.

Although this technique is quantitative and may be valuable, the measure of energy expended or absorbed in the joint does not give an insight into the internal conditions of the limb. However, it is possible to construct simple linear and non-linear models of internal joint dynamics that may provide a better measure of the causes of joint movement and hence the level of recovery.

3.2 Short duration force or position perturbations

Force or position perturbations can be used to estimate an impedance ($\mathbf{f} = Z(\mathbf{x}, \ldots, \ddot{\mathbf{x}})$ where force is a function of

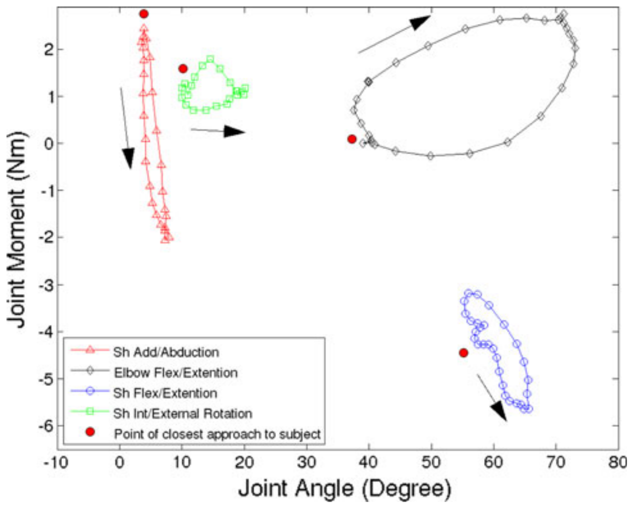

Fig. 3 Use of torque–position curves as an estimate of energy transfer in each joint (reproduced with permission)[27]. *Arrows* indicate direction of increasing time. Clockwise curves (elbow flex/ext) indicate the joint is expending energy to assist movement whereas anti-clockwise curves (shoulder) indicate that the joint is not contributing energy to the movement

position states such as velocity) or admittance, ($\mathbf{x} = A(\mathbf{f})$ where position (or a derivative) is a function of force states). Linear functions are often expressed in a state-space form or as functions of the Laplace domain variable, s. Typically these would be referred to either the joint space or a convenient Cartesian frame for the end point. A linear mass-spring-damper model is often used to characterise the admittance or impedance at joint or Cartesian endpoint level $f = (ms^2 + bs + k)x$ or $f = (ms + b + k/s)v$. Conversion between these two frames is straightforward so long as a Jacobian can be calculated. Thus if the joint admittance matrix is given by $\Delta\theta = \overset{j}{A}\tau$ (where the superscript j indicates that the admittance relates joint torque to joint angle).

$$\mathbf{f} = (J\overset{j}{A}J^{\mathrm{T}})^{-1}\Delta\mathbf{x} \tag{2}$$

Tsuji et al. [45] imposes a position perturbation over approximately 400 ms so it can be assumed that the figures for hand and hence joint impedance include both the mechanical response and an additional component due to the mono-synaptic and other reflexes. Tsuji considered impedance in a Cartesian framework and produced highly visual stiffness and viscosity maps in a subject's arms reachable workspace.

Bennett et al. [2] used perturbations from a pseudo-random air-jet to create torque perturbations that enabled an estimate of elbow stiffness changed during cyclical voluntary movements. Similar work by Zhang and Rymer [47] examined how elbow reflex-generated stiffness and viscosity contributed to the total stiffness of the joint. Their conclusion was that joint impedance is characterised by non-linearity and time-variance in healthy adults. Missing in all these studies is any concept of what causes these impedance changes. It is clear that there is both a mechanical and a neurological element but there has been little attempt to relate knowledge of the neuromuscular structures to the measurable impedance.

Impedance has been investigated in post-stroke subjects mainly in the absence of voluntary movements. McCrea et al. [28] measured a constant passive stiffness in chronic post-stroke subjects, thus gathering evidence in favour of a linear relation between torque and position. These results were similar to those obtained by Given et al. [13] for control subjects. McCrea also found a strong correlation between Modified Ashworth Scale indications of hypertonia and passive stiffness and damping, using a linear viscoelastic model.

Levin and Dimov [22] tested a step-unloading event on a control group and chronic post-stroke group, showing that stroke patients lacked agonist and antagonist muscle co-contraction immediately after releasing the load, pointing to a defective control of impedance. These results offer insight into some of the mechanism that are at the basis of motor control in hemiparetic subjects. They, however, lack longitudinal perspective and since they focus on chronic subjects (minimum 1 year after stroke) do not possess information on the mechanisms involved during the early stages of stroke recovery (first 5 months after stroke), when the majority of progress is made.

A technique with good specificity in identifying subsystems of arm movement is the concept of the parallel cascade model (Fig. 4 left) that considers a linear system to represent intrinsic dynamics and a parallel Hammerstein model[2] with delay to represent the reflex and higher neural elements [18]. Typically this is used in an impedance form but an equivalent admittance form is possible (Fig. 4 right). This second form is similar to the simulation studies done by Prochazka et al. [38].

The parallel cascade model was demonstrated by Mirbagheri [31] for the ankle, and relies on the fact that during the first 50–80 ms following a torque perturbation the response cannot have any conscious influence and hence represents underlying neuromuscular characteristics that can be compared to conventional clinical rehabilitation measurements. Achieving a measurable response in this time period is difficult, requiring either a well controlled and fast step position perturbation, or a large and short duration torque perturbation to produce a short position perturbation.

[2] A Hammerstein model is a simple non-linear model that consists of a static non-linear element that shapes the input variable, followed by a linear dynamic element.

Mirbagheri et al. [31] also described chronic post-stroke intrinsic and reflex stiffness of the elbow at different angular positions in the presence of perturbation but in the absence of movement. Using the parallel cascade model they were able to conclude that although intrinsic stiffness does not change between normal and post-stroke subjects (as observed in the linear pathway), reflex stiffness tends to increase in post-stroke individuals (as observed in the Hammerstein model of the reflex). In a further study they observe that it is possible to identify two groups from their data on elbow stiffness measurements of individuals in the 1 to 12-month period following their stroke. In the first group, the reflex stiffness and intrinsic gains increase consistently over the recovery period compared with the second group where these gains decrease [32]. The separation into these two groups remains somewhat arbitrary and the result can only be considered speculative at this stage.

Research by Burdet et al. [5] confirmed that stabilisation of the hand derives from stiffness adaptation during movements in the presence of a force field. These studies, although demonstrating that stiffness and viscosity are non-linear and time-varying for voluntary movements, do not however provide evidence on how the impedance of the individual joints of the arm changed during the reaching action, nor allow an insight into the parameters of key elements in an arm model.

3.3 Imposing learnable force perturbations

There are many theories as to how the brain controls movements, but a concept that has some validity is that in some circumstances the brain has the ability to encode a forward model—possibly in the cerebellum—and thereafter operates in essentially an open loop fashion [3, 30]. The signal sent by the motor cortex initiates the movements whilst proprioceptive signals are returned back to the motor cortex via the cerebellum in the course of the action (Fig. 5). The forward model theory then implicates the cerebellum in calculating the error between planned and actual sensory information using a pre-constituted dynamic model and sends this information to the motor cortex only where there is a discrepancy between computed and actual performance of the movement.

Evaluation of the brain's ability to encode these forward models is commonly done by investigating arm reaching movements in the presence of an external force field. One common form of force field is the so called 'curl' field. The usual methodology is to arrange a subject in front of a two axis manipulandum able to apply in the region of 3–15 N through a handle. The subject then makes a reaching movement towards a target and a perturbation force is applied. If the end point velocity of a manipulandum is $\dot{\mathbf{x}}$ then the force $\mathbf{f}$ that is applied through the handle or attachment point is computed as

$$\mathbf{f} = \begin{bmatrix} 0 & -\lambda \\ \lambda & 0 \end{bmatrix} \dot{\mathbf{x}} \tag{3}$$

and tends to distort movement in an anticlockwise direction (where λ is a scalar that dictates the level of distortion). Work by Shadmehr and Mussa-Ivaldi [42], Wolpert [46] and others has shown that the internal model required to compensate for this external environment can be learned in a relatively small number of movements (typically 10–15), and evidence that the model persists comes from the hand trajectory that occurs if the force perturbation is removed. Osu et al. showed that subjects were able to switch rapidly between models to compensate for a clockwise and a counter clockwise force perturbation [34].

The strength of this experimental scenario for stroke assessment is that it provides a method to observe through the 'curl' field both the mechanical processes needed to

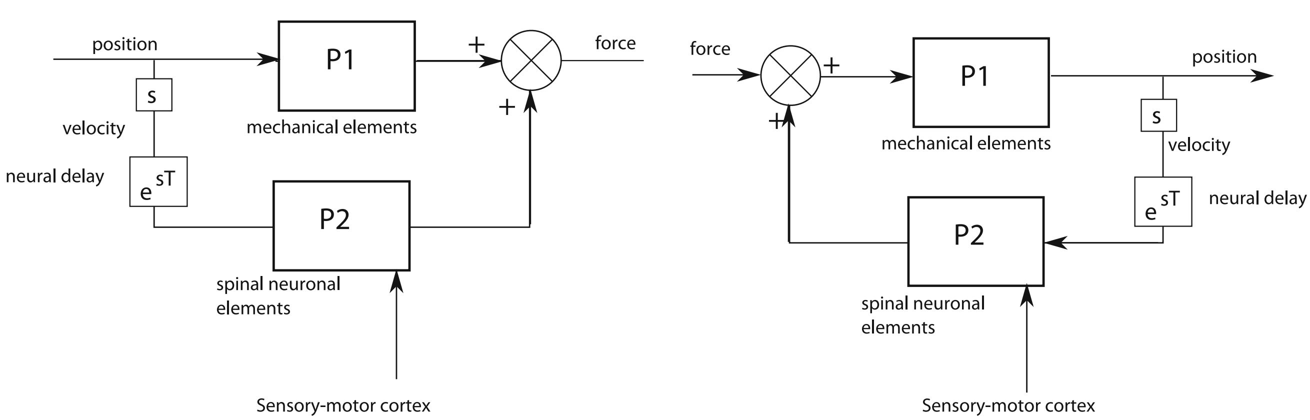

Fig. 4 Parallel cascade model (*left*) and Prochazka model structure (*right*). P1 is considered to model the effects of muscle, joint and surrounding tissue, and is represented as a linear model. P2 is considered to model the combination of reflexes and central nervous system, and is represented by a Hammerstein model

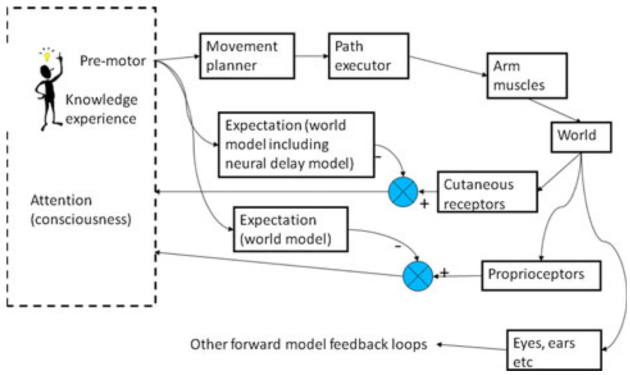

Fig. 5 Concept of forward models in the brain, e.g. [3]

make a reaching movement and the ability to use a forward model to compensate for the environment. It is clear that it will only be relevant to individuals who have made significant progress in recovering motor skills, and may not ever be relevant for people who have no potential to relearn movements, but its strength is the direct measurement in an unobtrusive way to make this assessment, potentially using the robot that is also delivering movement therapies.

Takahashi and Reinkensmeyer [44] considered such an assessment and noted that subjects had a decreased ability to learn the compensatory movements on their stroke effected side. They also observed that the inability to adapt to the curl field was well correlated to the severity of the stroke as assessed with the Chedoke-McMaster score.

Patton and Mussa-Ivaldi [36] used a similar approach to compare individuals with a stroke to age-matched controls. They did not find a correlation between the ability to learn an internal model and the Chedoke score, but observed that there was a correlation between the strength of the perturbing force and the ability to learn the model, and thus hypothesised that error-enhancing therapy may be more effective than constraining movement to a 'correct' path.

There were significant differences between these two studies that might account for the different conclusions, and in both cases the subjects were people with chronic stroke where less recovery is expected. This highlights the need for further research in the area, both to assess the sensitivity of a 'curl' field to a measure of limb recovery and to establish whether it can be used in a practical rehabilitation robot to both deliver treatment and as an assessment of recovery.

3.4 Assessing long-term skill learning

The force-based measurements described give some indication of neural activities but currently cannot be used to investigate long-term changes to the brain as a skill is acquired or relearned. Since stroke rehabilitation can be considered as a relearning process, knowledge of structural or connective changes in the brain will give an insight into this aspect of recovery. Techniques from brain imaging are able to show areas of the brain where structural (white/grey matter) changes occur. However, connectivity changes are almost impossible to determine in vitro, and only an indication is possible using brain imaging techniques that are sensitive to blood oxygenation levels that imply an increased metabolism of the neuronal cells.

Draganski et al. [7] and Scholz et al. [41] looked at skill acquisition using magnetic resonance imaging (MRI) studies to show that there is a long-term change to the grey and white matter in the brain that can be attributed to the acquisition of a motor skill [7, 41]. In both cases the acquired skill was cascade juggling and the intervention group were given 3 months (2004 a study on grey matter changes), or 6 weeks (2009 a study on white matter changes) to learn this new manual skill. These studies reported changes in the structure of the brain. Draganski's study of grey matter showed a change of mass in the mid-temporal area (hMT/V5) and left posterior intraparietal sulcus that could be attributed to the learned skill. Schultz reported a change of white matter in several areas including the right posterior intraparietal sulcus. Thus, the acquisition of a motor skill can be directly correlated to structural changes in the brain and it is these structural changes that must also occur when a person is re-acquiring motor skills during rehabilitation. A separate study by Boyke et al. [4] also looked at acquiring the skill of juggling, but in an elderly population . They experienced a high drop out rate and from the initial 93 subjects, they report data for a training group of 25 (age range 50–67 years) and a control group of 25 (age range 55–67 years). They reported changes to the grey matter in the middle temporal area of the visual cortex (hMT/V5).

Other skills also manifest structural changes, and Engvig [8] observed changes in cortical thickness (distance between the grey/white matter boundary and the pial surface) in elderly people (age range 42–77) following an 8 week training program designed to improve serial verbal recollection memory. Whether these techniques can be adapted to a specific measure of recovery, especially given the often non-localised damage to the brain, remains to be seen.

MRI measurements give no indication of the short term dynamics, so techniques such as near infra red spectroscopy (NIRS) and functional magnetic resonance imaging (fMRI) have emerged to measure changes in oxygenated blood flow. Both NIRS and fMRI can only be considered as an indication of neural activity since in both cases the signals are an ensemble of spatial and temporal activity from a large number of individual neurons. A further difficulty with fMRI based studies in movement is that it is difficult to gather valid data from subjects whilst they are in the coils. Problems are associated with the slow response of the signals, the corruption of the signals caused as a result of the subject moving and from the distortion of the magnetic fields produced by most metals. This has not prevented several attempts at producing haptic devices that are compatible with MRI and fMRI measurements [12, 15, 20]. Resolving this difficulty would allow a much greater correlation of the cognitive process to those that generate the motor patterns for volitional movements.

4 Discussion

For the foreseeable future validated clinical measures are likely to remain the only accepted method for evaluating the benefits of an intervention intended to retrain movements following a stroke. However, there is a second purpose for validated clinical measures, that is as a way to monitor the recovery of an individual and make decisions about appropriate treatments. Just as machine mediated stroke interventions are required to show a value in either saving costs or enhancing treatment, any measurements of the recovery progress must be easy to administer and produce useful information for clinical decision making. Although there is large literature on assessment techniques, it is not appropriate to simply adapt these so they can be delivered mechanically, rather the opportunity exists to use knowledge from human motor control to attempt to get at more fundamental processes associated with relearning or retraining movements. There are unique advantages for machine-based assessment techniques. The first is the ability to collect large quantities of data. However, data do not always translate to information and further work is needed to identify what measurements will compute useful, consistent and reliable metrics of recovery. The second advantage is that machine-based measures will be objective and quantitative. Where the measure is only for clinical assessment this can be considered an advantage, but there is interest in investigating reward systems for people undergoing stroke rehabilitation. A therapist who has access to a clinical measure can use discretion in deciding whether or not to pass this information on to the patient. Likewise the same therapist may be better able to judge if a metric is incorrect, based on a more complete knowledge of the person.

If the machine-assisted intervention therapy can be integrated with methods to make mechanical assessment of recovery, an additional advantage will be that a measurement can be taken at almost any time. This is akin to the 'catch trials' used when assessing the learning of a perturbation model, the force perturbation is turned off and the response in this condition measured. Likewise at appropriate points in an intervention therapy it would be possible to reduce the levels of assistance and insert the forces or position perturbations needed to assess the recovery.

Further study is needed to develop strategies for gathering useful data for machine measures. The relatively straight forward estimation of energy transfers used by Mak et al. [27] should transfer readily across a range of devices. It is more complex to design rehabilitation robots that can deliver consistent force or position perturbations across the different configurations of device, in particular given that differing levels and durations of force perturbation were conjectured by Patton and Mussa-Ivaldi [36] to have different learning effects on the individual. However, the potential of embedding the necessary hardware, control and processing into rehabilitation equipment to allow consistent measurement of features that have a clinical relevance will strengthen the case for the introduction of intelligent machines in neurorehabilitation.

Robots and intelligent machines clearly have a contribution to make in stroke rehabilitation but these benefits should not be confined simply to delivering therapies, but should be used to enhance the abilities of the therapist as well as to make a more precise assessment of recovery. The best techniques for assessment still need to be determined, but will work most effectively if they are reliable, open,verifiable and independent of any particular stroke rehabilitation product. Combining information from clinical, mechanical and brain imagery measurements will then allow all aspects of stroke recovery to be considered.

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