

How to Retrain Movement after Neurologic Injury: A Computational Rationale for Incorporating Robot (or Therapist) Assistance

D.J. Reinkensmeyer

Dept. of Mechanical and Aerospace Engineering, Center for Biomedical Engineering University of California, Irvine, USA

Abstract— This paper develops an adaptive Markov model of sensory motor control, and then uses the model to examine the putative role of external mechanical assistance from a robotic device or therapist in promoting neurologic recovery. The model assumes that: 1) The CNS probabilistically interprets proprioceptive information in real time in order to generate motor output; 2) Sensory-motor pathways become more reliable with repetitive activation in a sort of Hebbian learning; 3) Normal sensory input sometimes elicits abnormal motor output following neurologic injury due to disrupted neural organization. The model predicts the best movement recovery when an external trainer intervenes to correct errant movements on an “as-needed” basis, compared to no or continual assistance. The model thus provides a computational rationale for incorporating mechanical assistance on an as-needed basis during neurorehabilitation therapy.

Keywords— Neurorehabilitation, movement control, robotics

I. INTRODUCTION

It is becoming increasingly clear that the central nervous system can be assisted in reprogramming itself to control movement following injury with intensive rehabilitation therapy [1,2]. However, it is currently unclear what the optimal reprogramming techniques are. Both conventional and innovative therapy techniques speak of “assisting the patient’s movement only when needed” and “eliciting normative sensory input to enhance motor output” [3,4], but few controlled studies have tested these principles. Recent successful attempts at automating movement therapy with robotic devices have also focused on mechanically assisting patient arm or leg movement [5]. It is unclear, however, whether the mechanical assistance provided by the robotic devices, as opposed to the repetitive movement attempts by the patient or some other factor was the primary

stimulus for the observed movement recovery [6].

This paper presents a computational framework for understanding the putative role of mechanical assistance in promoting movement recovery following neurologic injury. An adaptive Markov model of sensory motor control is derived based on biologically plausible principles. The model is then used to identify conditions under which mechanical assistance might be expected to improve movement recovery.

II. METHODS

The model is based on several key assumptions:

Assumption 1: Proprioception Drives Motor Output

The first key assumption is that proprioceptive information directly shapes motor output in real-time during movement. This assumption is captured abstractly using a Markov model in which movement control is a probabilistic, iterative process of transformation from sensory to motor states and vice versa (Fig. 1a). The central nervous system mediates the sensory to motor transitions by interpreting the pattern of sensory input and selecting a motor output. Muscle and limb dynamics mediate the motor to sensory transitions.

To place this abstraction into a specific context, consider how proprioceptive information shapes locomotor output in spinal-injured humans and animals [7]. Changes in load-related afferent information during spinal locomotion causes functionally appropriate levels of limb extensor muscle activity to support the body. Hip extension angle information plays a key role in triggering the transition from stance to swing. Cutaneous input to the foot triggers a flexion withdrawal or extensor thrust response

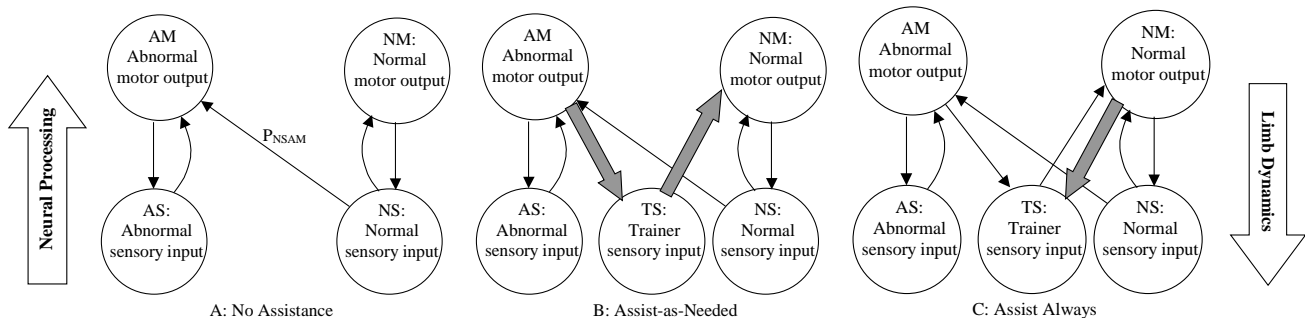


Figure 1 Computational model of sensory motor control. A) The model assumes that the nervous system interprets proprioceptive information in order to create motor output, and that motor output in turn creates sensory input. Motor and sensory states are abstracted into “normal” and “abnormal” states. The transitions between sensory and motor states are probabilistic, and the probabilities are modified with use in a Hebbian manner, resulting in an adaptive, Markov model. One such transition probability, P_{NSAM} , is shown. The same notation is used throughout the paper to refer to other transition probabilities. B) An external trainer (a therapist or robot) intervenes by recognizing abnormal motor output, assisting the limb and thereby creating a novel sensory state TS, which leads to a normal motor output. C) A trainer that assists always intervenes even when motor output is normal.

appropriate to the phase of gait during which the cutaneous input occurs. These examples illustrate a tight link between proprioceptive input and motor output, consistent with the state transition framework of the model.

For simplicity, the model abstracts sensory and motor states into two categories: “normal” and “abnormal” (Fig. 1a). Abnormal sensory and motor states are associated with impaired movement following neurologic injury. For example, in the locomotion example, injury may impair the spinal cord’s ability to process load-related afferent information. This impaired information, an abnormal sensory state, leads to impaired regulation of extensor activity during stance, an impaired motor state. The impaired motor state (the leg collapsing), in turn leads to abnormal sensory input (reduced load-related information). When the nervous system is functionally intact, normative sensory input typically causes normative motor output and vice versa. However, the transitions from sensory to motor states in the model remain probabilistic, reflecting the inherent noise in neural processing.

Assumption 2: Injury Disrupts Sensory Motor Coupling

To model the effects of neurologic injury, the model assumes that normal sensory input doesn’t always cause a normal motor output following neurologic injury. The transition probability PNSNM (Fig. 1a) reflects the severity of the impairment, with smaller PNSNM reflecting greater impairment. This assumption captures the observation that neurologic injury alters sensory motor circuits via destruction of descending inhibitory or excitatory pathways, remodeling of synaptic connectivity, or direct damage to motor control circuits themselves.

Assumption 3: Sensory Motor Pathways Become More Reliable with Use To model neural plasticity, the probabilities for sensory motor transitions – i.e. the transitions implemented by the nervous system – are incremented by a small amount each time the pathways are traversed. This adaptation corresponds to the hypothesis that sensory motor pathways are reinforced or become more reliable when used, a form of Hebbian Learning in the sense of long-lasting changes in connectivity due to correlated input and output activity. The transition probabilities associated with competing sensory motor pathways are reduced by an equivalent amount.

Assumption 4: An External Trainer Creates Normal Motor Output The action of a human or robotic trainer is incorporated into the model as a transition from an abnormal motor state to a novel sensory state (TS) with probability one (PAMTS = 1, Fig. 1b). In other words, the trainer observes the abnormal motor output and mechanically intervenes to correct it. TS is a state representing trainer-induced sensory input, which captures the concept that the trainer necessarily alters tactile and proprioceptive input by moving the limb, thus creating a novel sensory state. Initially it is assumed that the trainer alters the patient’s movement and thus proprioceptive input in such a way so that the patient subsequently performs a normative

movement (PTSNM = 1), although the probability of triggering a normal movement will be lowered to determine vary the trainer’s “skill level”.

To give a concrete example of this abstract implementation of trainer assistance, human trainers closely monitor leg extension of the patient during stance during locomotor training with body weight support [4]. If the patient begins to collapse, the trainer manually prevents knee flexion by pushing on the knee. This intervention not only preserves the kinematics of the leg during stance, but also introduces additional proprioceptive inputs from stretch and load receptors in the patella tendon that facilitate leg extension via stretch reflex pathways. Thus, the trainer intervenes when needed, creating a normative motor output, but also introducing a novel sensory state.

Other Assumptions: The model assumes that the motor to sensory transitions implemented by the limb dynamics are causal (PAMAS = 1, PNMNS = 1). It also assumes initially that abnormal sensory input invariably causes abnormal motor output (PASAM = 1). This latter assumption implements a tight coupling between sensory input and motor output, which will be relaxed later.

Simulation Protocol: To characterize the model response, the initial state was chosen to be MA, and the model was run for 10,000 state transitions using a pseudorandom number generator and the state transition probabilities to select state transitions. Each time a sensory to motor transition was made, the probability of that transition was incremented by 0.001, and the probability of competing pathways was decremented by an equal amount. For simulations in which therapy was provided, therapy was initiated at transition 2000 and terminated at transition 8000. The percent time spent in state NM versus AM was averaged across a window of 100 transitions, which was defined as a single “therapy session”. This process was repeated for 10 virtual subjects, and the mean was taken across subjects. Thus, the results shown below are averages across sessions and subjects, with “therapy” beginning at session 20 and ending at session 80.

III. RESULTS

Consider first the baseline model shown in Fig. 1a, which represents a neurologically impaired sensory motor system with no external assistance. Assume the subject initiates a normal movement (NM), creating a normal sensory state (NS). If PNSNM is less than one, there is a finite probability that the normal sensory information will trigger an abnormal motor state. Once the transition from NS to AM is made, it is impossible to leave the AM-AS loop because PASAM = 1. Thus, the normative sensory motor pathway NS-NM is unused and unaltered, and only the abnormal sensory-motor pathway is reinforced (Fig. 2).

The model predicts that recovery can be facilitated by mechanically assisting abnormal movements. If assistance is provided only when an abnormal motor state is entered as shown in Fig. 1b, then normal motor states are experienced

when assistance is provided, but also following “therapy” (Fig. 2), demonstrating a persisting change in the sensory motor transition probabilities.

The mechanism of this recovery is that assistance-as-needed prevents iterative excitation of the AM-AS loop, instead causing either the NS-AM or NS-NM transition to be excited. If $P_{NSNM} > 0.5$, then the NS-NM transition will be experienced more often than the NS-AM transition, and therefore P_{NSNM} will grow larger and P_{NSAM} smaller, since sensory-motor pathways are incrementally strengthened each time that they are used, and weakened by excitation of competing pathways. Put another way, the model predicts that assistance provided “as needed” improves sensory motor recovery for simulated patients who are not too impaired; i.e. for patients for whom normal sensory input continues to be more likely to cause normal rather than abnormal motor output.

What happens if the trainer provides assistance indiscriminately, assisting even when the patient generates a normal motor output (Fig. 1c)? In this situation, the NS-NM transition is never experienced and thus never strengthened. Motor performance improves during therapy (Fig. 2), but this performance improvement does not transfer following therapy because the key NS-NM sensory motor pathway remains unaltered.

The trainer’s skill can be modeled as the probability of eliciting a normal motor output from the trainer-induced sensory state (P_{TSNM}). As can be seen in Figure 4, the trainer’s skill level influences whether “assistance-as-needed therapy” has a benefit. Less skilled therapists (P_{TSNM} small) only help less impaired subjects (P_{NSNM} large). Even highly skilled therapists (P_{TSNM} large) cannot help severely impaired subjects ($P_{NSNM} < .5$).

Insight can also be gained into neural systems for which proprioceptive information plays a reduced role in shaping

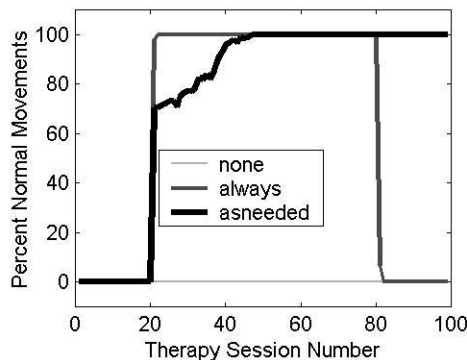


Figure 2 Comparison of no assistance, assist-as-needed, and always-assisting strategies. Lines are means calculated from simulating the three models in Fig. 1 ten times each for 10,000 state transitions (100 transitions/“therapy session”). The probability P_{NSNM} was initially 0.6. “As-needed” and “always” assist therapy began at session 20 and ended at 80.

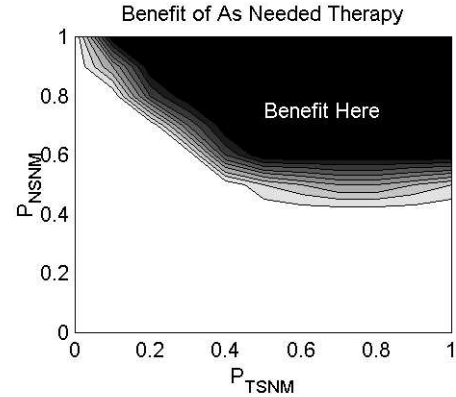


Figure 3 Active assist benefit depends on skill level of trainer. Dark area shows where as needed therapy provides a benefit.

motor output. The probability that abnormal sensory input causes an abnormal motor output (P_{ASAM}) would be low for a system driven by feedforward control processes rather than by proprioceptive feedback; in other words, for such a system, even extraneous or erroneous proprioceptive input should not affect motor output. Figure 4 compares the effects of no assistance, assistance-as-needed, and always assisting across a range of values for P_{NSNM} (which quantifies the “impairment” level) and P_{ASAM} (which quantifies the “sensory-motor coupling” level). Note that no recovery is possible with any of the assistance techniques for severely impaired virtual patients ($P_{NSNM} < .5$). Assistance-as-needed is uniquely beneficial for mildly/moderately-impaired virtual patients ($P_{NSNM} > .5$) with strong sensory motor coupling (P_{ASAM} large). However, for mildly/moderately impaired patients and weak sensory motor coupling, “no assistance” and “always-assisting” are just as effective as assistance “as-needed.”

IV. DISCUSSION AND CONCLUSION

There are substantial efforts underway to build robotic devices to automate hands-on movement therapy [5]. However, there are few or no mathematical models that provide a rationale for providing external mechanical assistance during rehabilitation therapy. This paper provides such a model at a computational level of analysis. Based on the biologically plausible principles of sensory motor coupling, Hebbian learning, and neural disorganization following injury, the model makes predictions that correspond well with current intuition and recent research results. These predictions are:

Prediction 1: Assistance when needed can enhance recovery. Recovery can be enhanced by a trainer who actively assists abnormal movements, if the patient’s sensory motor impairment is not too severe ($P_{NSAM} < .5$). This prediction corresponds well to recent robotic- and therapist-based studies that have successfully used external mechanical assistance to retrain arm or locomotor ability after stroke and spinal cord injury [5].

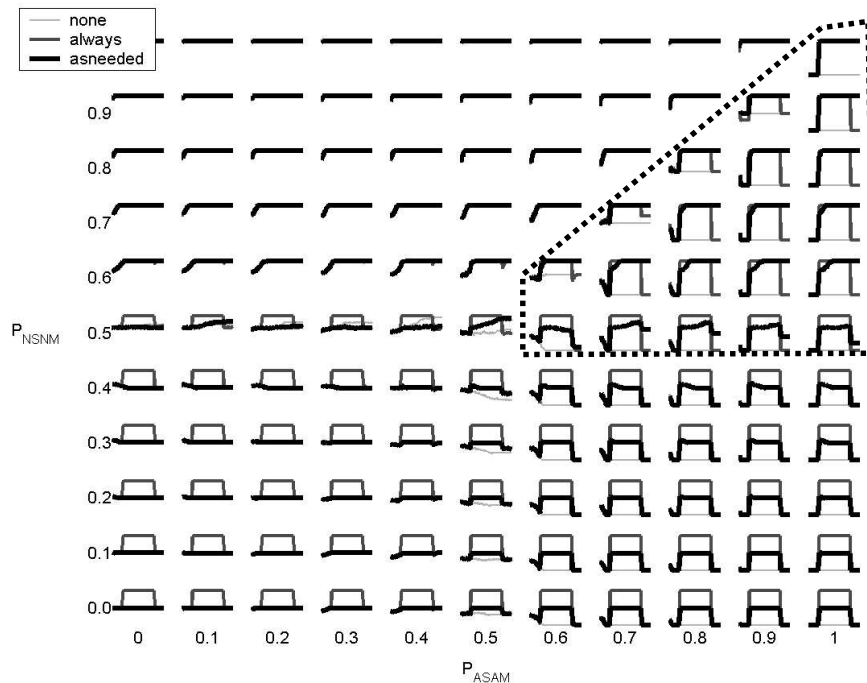


Figure 4 Comparison of no assistance, assist-as-needed, and always-assisting strategies for a range of impairment levels (PNSNM) and levels of sensory motor coupling (PASAM). The subplots show the percentage of normal movements for the three strategies, before, during, and after therapy, with the same scales as Figure 2. No strategy improves motor performance for severely impaired virtual patients (PNSNM < .5). The assist-as-needed strategy is differentially beneficial in the dashed region. All three strategies are equivalent (i.e. the three lines overlay) for weak sensory motor coupling (PASAM small) and mild/moderate impairment (PNSNM large).

Prediction 2: Always assisting is not as effective as assistance when needed. Blindly assisting every movement of a patient is never beneficial compared to no assistance or assistance-as-needed, although it is equivalent in some situations (Fig. 4). This prediction corresponds to the intuition that a therapist or robotic device that does not grade the level of assistance provided will not be as effective as one that does.

Prediction 3: The trainer's skill matters. Less skilled trainers only help less impaired subjects, consistent with expert therapists' impressions that the precise patterns of sensory input provided during assistance are important.

Prediction 4: Active assistance is unnecessary when sensory input is not directly coupled to motor output. For a system in which abnormal sensory input doesn't always cause abnormal motor output ($P_{ASAM} < 1$), recovery does not require external assistance. This prediction suggests that there is a fundamental difference in the optimal therapy approach for different sensory motor systems. For example, attempts to retrain locomotion after spinal cord injury may benefit from active assistance because of the relatively tight coupling of proprioceptive input and motor output in locomotion [7]. In contrast, attempts to retrain arm movement after stroke may benefit less from active assistance, because proprioceptive information may play a less direct role in shaping motor output for the arm. Specifically, feedforward mechanisms are largely sufficient to arm movements [8]. Note that the model predicts that external assistance is not detrimental for uncoupled systems, but only that it is unnecessary, because unassisted, repetitive movement practice produces an equivalent result. This prediction has important practical ramifications because assistance requires substantial human or machine overhead.

Some of the limitations of the model are its use of only "abnormal" and "normal" states, its grouping of all sensory input into a single sensory state, and its assumption that the trainer creates a wholly novel sensory state. The model can be expanded to address these limitations. However, the core prediction will likely stay the same: mechanical assistance incorporated on an as-needed basis is beneficial for systems with strong proprioceptive-motor coupling.

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