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Reinforcement-Induced Movement Therapy: A novel approach for overcoming learned non-use in chronic stroke patients

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Abstract—An open question in stroke rehabilitation is, if and how chronic patients can still make improvements after they reached a plateau in motor recovery. Previous research has shown that Constraint-Induced Movement Therapy (CIMT) might be effective in treating hemiparesis and supporting functional improvements in chronic patients, but that it might also be associated with higher costs in terms of demand, resources and inconvenience for the patient. Here, we offer a new therapeutic approach that combines CIMT with a positive reinforcement component. We suggest that this new therapy, called Reinforcement-Induced Movement Therapy (RIMT), might be similarly effective as CIMT and could be suitable for a broader population of chronic stroke patients. We first implemented a computational model to study the potential outcome of different CIMT and RIMT therapy combinations. Then we present the results of an ongoing clinical trial that supports predictions from the model. We conclude that an optimally combined CIMT and RIMT therapy might propose a novel and powerful rehabilitation approach, addressing the specific needs of chronic stroke patients.

I. INTRODUCTION

Worldwide every year almost 15 million of people experience a stroke [1]. Of these, about 5 million are left permanently disabled and require subsequent rehabilitation for a number of impairments. Hemiparesis is one of the most common impairments after a stroke, affecting about 80% of stroke survivors. Many rehabilitation practices have proven to be effective in reducing hemiparesis and improving the quality of life of stroke patients.

Constraint-Induced Movement Therapy (CIMT), which forces the use of the paretic limb by constraining the movement of the non-paretic limb, has previously been shown to produce substantial improvements at the chronic phase post-stroke, suggesting that tendency to plateau in motor recovery does not indicate a similar plateau in functional improvements [2]. The procedure behind CIMT protocols, also called ”shaping”, is based on the principle that a prolonged non-use of the affected limb may cause the loss of its motor function, initiating a vicious cycle in which non-use and poor performance reinforce each other. Even though this principle has been widely accepted in literature, multiple studies have questioned CIMT techniques, considering them too demanding, costly in terms of resources, and even inconvenient for severely impaired patients [3], [4], [5]. Therefore new therapeutic strategies should be designed, that exploit the unique benefits of the CIMT principles and overcome its limitations in implementation.

In this study, we propose that alternative methods to CIMT, such as reward-based treatments, may be similarly efficient for the improvement of motor function. We define a novel rehabilitative technique for promoting the use of the paretic limb, termed ”Reinforcement-Induced Movement Therapy” (RIMT). It is characterized by the increase of expected rewards associated to action execution using the paretic limb. One possible method for implementing RIMT is the amplification of goal-oriented movements executed with the paretic limb. In this line, RIMT exposes the patient to a diminished visuomotor error when using the paretic limb, influencing the patient’s perceived performance, and promoting its future use. In this line, a computational model of stroke motor recovery proposed that after performance reaches a threshold, a spontaneous process of functional recovery is initiated [6], [7]. In the model authors used CIMT as a method for triggering the so-called virtuous cycle of recovery, in which improvements in performance stimulate the use of the paretic limb and vice versa. We postulate that the principles implemented in this model predict the efficacy of RIMT protocols.

In order to implement a technique for providing RIMT, we
created a method for modulating visuomotor feedback using a VR-based rehabilitation tool, the Rehabilitation Gaming System (RGS) [8], [9]. RGS integrates a paradigm of action execution and action observation. That is, the user controls a virtual body (avatar) seen from a first-person perspective on a screen. Execution of goal-directed movement is thus coordinated with observation of the same movement. The rationale for the action-observation paradigm is based on the neurologic considerations that plasticity of the brain can be utilized to achieve functional reorganization of the brain areas affected by stroke, and can be enhanced by means of activation of secondary motor areas such as the so-called mirror neuron system [10], [11].

We hypothesize that RIMT and CIMT protocols can be combined to promote the use of the paretic limb and induce functional gains after stroke. In order to explore this hypothesis, we first describe a computational model to predict motor recovery after stroke, comparing and combining the effects of CIMT and RIMT. The model allows us to analyze the optimal combination of the two therapies for an effective rehabilitation. Further it provides hand selection patterns on a trial-by-trial basis. We compare these results with behavioral data from an ongoing randomized, double-blind, longitudinal clinical study where stroke patients performed motor training using RGS, and we analyze the effects of RIMT on countering learned non-use and motor impairments.

II. METHODS

A. Computer Simulation Methods

We have implemented a computational model of motor recovery based on [6]. Han et al. proposed a model that makes predictions of long-term changes in arm use as a function of directional accuracy. Simulations compute performance of planar unimanual reaching movements towards targets appearing along a circle. After performance, reward prediction errors update expected action values in order to optimize future performance. We extended this model by integrating the planing of movement extent as an indicator of motor performance, and by incorporating the expected cost of a movement as a parameter for action selection. Figure 1 depicts the main components of our model: lateralized cortical motor areas for motor planing, a cost estimation unit, and an action selection module. Cortical motor areas receive information about the direction of a reachable target and plan the corresponding movement; the cost estimation unit transforms the planned movement to intrinsic coordinates and estimates the energy that would be needed for its execution; finally, two networks within the action selection module accumulate activity for two competing actions (i.e. executing the movement planned for the right or the left limb) taking into account expected rewards and energies for both actions.

1) Motor Performance: In this model, motor cortex is formed by two lateralized motor networks of direction-tuned cells, which generate vectorial planned movement trajectories and reorganize to minimize error though practice, in terms of both movement extent (i.e. length of the movement trajectory) and direction.

In reaching movements, movement extent and direction have different sources of variable and systematic errors [12], [13], suggesting that hand paths are initially planned in vectorial coordinates without taking into account joint motions. In our model we implemented in each hemisphere of the motor cortex two networks of neurons sensitive to specific directions, one codes the extent and the other codes the direction of a planned trajectory. The activity of each motor neuron is determined by the difference between the preferred direction of neuron $\theta^p_i$ and the desired movement direction $\theta_d$ [6], [14]:

$$y = [\cos(\theta_d - \theta^p_i) + N(0, \sigma_{SDN}^i)]^+$$

where $[x]^+ = x$, if $x > 0$

$$0, \text{ if } x < 0$$

In the network coding movement extent, the length of the planed movement trajectory is determined by the weighted sum of activity of each neuron $i$ in the network. Each weight $w_i$ updates after execution as a function of error in extent given the activity of neuron $i$, rapidly adjusting to the optimal extent of an angle dependent trajectory:

$$\delta w_i = \eta(X_e - X_d)y_i(\theta_d, \theta^p_i).$$

where $\eta$ is a learning rate, $X_e$ is the executed movement extent, and $X_d$ is the desired movement extent (i.e. the actual extent needed to reach the target position). Each of this
networks contained 20 neurons, and the learning rate $\eta$ was set at 0.5.

In the network coding movement direction, the angle for the planned trajectory is the vector sum of the activity of each neuron $i$, and follows the same method as reported in [6]. After execution, a combination of error-based and use-dependent learning updates the motor cortex contra-lateral to the selected limb, modulating the preferred angles of motor neurons to enhance performance accuracy in the future execution of similar movements. Each of these networks contained 500 neurons with uniformly distributed angle sensitivities (0-360 degrees). For the parameters in this network we used the same values reported in [6].

2) Estimation of Energies: In the last decade, several authors referred to the general hypothesis that the nervous system optimizes performance as a function of energy expenditure [15], [16], [17]. Following this line, a previous study showed that humans prefer to select reaching movements which are biomechanically easier to perform [18]. This implies that the brain codes information about the future biomechanical costs of multiple movements, before deciding which one to execute. To account for this bias in action selection an independent unit in our model estimates the energies needed to achieve each planned joint angle. First, we add a unit in the motor cortex which performs the transformation of planed movements from vectorial coordinates to intrinsic coordinates. In order to compute the interaction torques produced at each joint by motions of upper arm and forearm segments we use the method described in [19] modified to account only for planar reaching movements with fixed shoulder positions (i.e. constrained trunk movements). Interaction torques for shoulder ($T_s$) and elbow ($T_e$) for each limb $h$ (i.e. left or right) are given by:

$$T_{h,s} = \alpha \dot{\theta}_s + \beta \dot{\theta}_e + \gamma \ddot{\theta}_e - 2s \gamma \dot{\theta}_s \dot{\theta}_e T_{h,e} = \epsilon \dot{\theta}_e + \beta \dot{\theta}_s + \gamma \ddot{\theta}_s$$

where

$$\alpha = m_s r_s^2 + I_s + m_e (l_s^2 + r_s^2 + 2l_s r_s \cos(\theta_c)) + I_e$$

$$\beta = m_e l_c r_c \cos(\theta_c) + m_e r_e^2 + I_e$$

$$\gamma = m_e l_c r_c \sin(\theta_c)$$

$$\epsilon = m_e r_e^2 + I_e$$

This transformation needs to take into account the anthropometric properties of the moving arm (mass of upper-arm $m_s$, mass of fore-arm $m_e$, center of mass of upper arm $r_s$ and forearm $r_e$, length of upper arm $l_s$ and forearm $l_e$, and moments of inertia at center of mass of the upper arm $I_s$ and forearm $I_e$). We used anthropometrical data from [20].

The expected energies for a specific action $\alpha$ are computed as the sum of the multiplication of jerks ($\ddot{\theta}$) and torques ($T$) for shoulder and elbow at each time step $t$ until the final time step $n$:

$$E_\alpha = \sum_{t=0}^{n} T_s(t) \ddot{\theta}_s(t) + T_e(t) \ddot{\theta}_e(t)$$

3) Action Selection: The action selection module is a variation of an interactive race model [21] divided in two competing units corresponding to two possible actions (i.e. reaching with the left limb or with the right limb). Each of them recursively accumulates action-specific activity $A_{a,h}$ for each hand $h$ given the expected reward of this action. In addition, it is recursively inhibited by the competing action network activity. As a result, targets appearing at left or right workspace will show higher probably of being reached by the ipsilateral hand. In addition, a noise term, $N$, is added to represent noise in input to account for exploration in action selection. Activity ($A_{a,h}$) for action $a$ (i.e. joints rotations for reaching towards an specific location) and limb $h$ is given by:

$$A_{a,h}(t) = A_{a,h}(t-1) + s_r Q_{a,h} - s_e E_{a,h} - s_a A_{a,h-1}(t) + N(t)$$

where $Q_{a,h}$ is the expected reward, and $A_{a,h-1}$ is the accumulated activity for the competing action (i.e. selecting the other hand). $s_r$, $s_e$, and $s_a$ are scalars for the expected reward, expected energies and activity of the competing action respectively. This accumulation of activity in the action selection module simulates an increase in striatal dopamine, which outputs an action choice after reaching a threshold [22].

After action execution, the expected reward for the selected movement is updated in memory given the reward prediction error, that is, the difference between the actual reward $R$ and the expected reward $Q$ retrieved from memory [6]. These updates minimize the square of the reward prediction error. For the acquisition of expected rewards $Q$ we used the same methods and parameters reported in [6]. Scalars used in the action selection rule were $s_r = 0.4$, $s_e = 100$, and $s_a = 0.7$. Scalar values were found to provide greater influence for action selection to the expected reward, followed by expected energies and the activity of the competing action. Noise in the interactive race model is normally distributed, with zero mean and standard deviation 0.15, and threshold for action selection was set to 1.

B. Clinical Study

In order to confirm predictions from the model we designed a randomized, double-blind, longitudinal clinical study.

| TABLE I. PARTICIPANTS DEMOGRAPHICS AND SCORES FROM CLINICAL SCALES AT BASELINE. |
|-------------------------------------------------|--------|--------|--------|
| Gender (male/female)   | RIMT (n=5) | Control (n=5) | p-val* |
| Age                   | 50     | 41     | -      |
| Impaired limb (left/right) | 59.4 ± 9.5 | 61.4 ± 4.7 | > 0.1 |
| Type (ischemic/haemorrhagic) | 2/3  | 3/2  | -      |
| MRC proximal [23]       | 3.8 ± 0.57 | 4.2 ± 0.27 | > 0.1 |
| FM [24]                | 33.2 ± 16.16 | 36.1 ± 11.07 | > 0.1 |
| CAHAI [25]             | 35.6 ± 15.55 | 32.2 ± 15.80 | > 0.1 |
| Barthel [26]           | 82.5 ± 9.98 | 85.75 ± 6.45 | > 0.1 |
| Hamilton [27]          | 12.6 ± 7.37 | 10.75 ± 8.85 | > 0.1 |
| Ashworth proximal [28]  | 3/2    | 3/2    | -      |

*Wilcoxon rank-sum test. MRC: Medical Research Council, FM: The Fugl-Meyer Assessment, CAHAI: Chedoke Arm and Hand Activity Inventory.
Its main objective was to assess the impact of combining Reinforcement-Induced Movement Therapy (RIMT) and Constraint-Induced Movement Therapy (CIMT) to promote motor recovery and treat learned non-use. This study is an ongoing clinical trial and we report only a subset of the results.

1) Participants: Participants were recruited from the rehabilitation unit at Hospital Joan XXIII, from Tarragona, Spain. Ten chronic stroke patients accepted to participate in the study (Table 1). All participants provided written consent prior to participation in the study. Inclusion criteria were as follows: a) Upper limb hemiparesis secondary to a first-ever ischemic stroke (> 4 weeks post-stroke); b) Proximal upper limb motor deficit (Medical Research Council Scale for muscle strength > 3); c) Age between 45 and 85 years old; and d) Absence of any major cognitive impairment (Mini Mental State Evaluation > 22). The ethics committee of clinical research from Hospital Universitari Joan XXIII approved experimental guidelines.

2) Setup and Experimental Design: Within the frame of the Rehabilitation Gaming System (RGS) (Fig.1A), we developed three training scenarios (Fig.1C-E): Spheroids, Collector, and Wack-a-mole. In all scenarios, the parameters defining task difficulty were adjusted automatically to provide customized training intensity depending on individuals’ capabilities (description of methods in [29]). Scores were always displayed on the upper-right corner of the screen and accumulated across trials. During Spheroids and Collector scenarios patients were instructed to intercept spheres and bubbles by performing horizontal arm movements. In both scenarios the screen was divided in two workspaces, only allowing for ipsilateral movements, thus forcing the user to use one limb or the other depending on the location of the target. Therefore the type of training provided by these scenarios was based on the mass practice and shaping principles proposed by CIMT. Occasionally, multiple targets would appear simultaneously at both workspaces in the VR-scenario, promoting bimanual training.

The Wack-a-mole scenario served not only to provide motor training but also as a tool for the evaluation of hand selection patterns. In this scenario patients had to perform planar reaching movements in order to strike appearing moles. Participants were able to freely choose which limb to use independently of the location of the target, therefore allowing for both ipsilateral and contralateral movements. Two red cylinders indicated the start positions for the hands (7.5 cm in diameter and placed 48 cm apart). After the subject maintained the avatar’s hands over the start positions during a variable time interval of $1 \pm 0.5$ s the two red cylinders disappeared and a target (i.e. a mole) appeared at any of nine possible angles ($0, \pm 4, \pm 8, \pm 10$, and $\pm 32$ degrees) along a semicircular array 65 cm from the projected center of the avatar. Trial time limits were set to 1.75 s. If the avatar’s hand successfully reached the mole within this time window, the mole disappeared and a sound indicated the success while the score increased by 30 points every tenth of a second.
Participants were assigned to two groups (RIMT or Control) with balanced randomization. Both groups performed a training program with RGS during 6 weeks, consisting of 5 weekly sessions of 30 minutes each. Within each session, patients trained in the three rehabilitation scenarios described above, which frequently forced the subjects to use the paretic limb. In addition, group RIMT experienced a goal-oriented amplification of the movement of the virtual analog of the paretic limb during training, therefore being exposed to diminished visuomotor errors. The control group experienced a non-modulated mapping of upper-limbs movements in VR. Notice that while patients in the control group were frequently forced to use the paretic limb, patients in the RIMT group were not only forced but also reinforced to use the paretic limb. All patients’ motor and cognitive function was evaluated before treatment (baseline), at week 6 (end of the rehabilitation program), and at week 12 follow-up, in four standard clinical scales: Fugl-Meyer Assessment (FM), Chedoke Arm and Hand Activity Inventory (CAHAI), Barthel Index (BI), and Hamilton.

3) Movement Amplification: For providing RIMT, in this study we implement a reinforcement technique based on the reduction of error-feedback during goal-oriented movements. This modulation was only applied when movements were executed using the paretic limb. In order to achieve this effect, we modulated visuomotor feedback by amplifying the movement of the virtual limb both in accuracy and extent. At each frame, we multiplied the executed vector (\( \mathbf{m}_e \)) by a constant gain factor \( G \). We projected the resulting vector (\( \mathbf{m}_a \)) over the target vector (\( \mathbf{t} \)), obtaining the vector (\( \mathbf{m}_p \)). Finally we determined the amount of augmentation to be applied at the current timeframe by:

\[
\mathbf{m}_a = \alpha \cdot \mathbf{m}_p + (1 - \alpha) \mathbf{m}_e
\]

where \( \alpha = \frac{|\mathbf{m}_p|}{|\mathbf{t}|} \cdot H \)

where \( H \) is a constant help factor. Notice that the movement amplification vector \( \mathbf{m}_a \) is a weighted combination of two terms: an accuracy amplification vector and an extent amplification vector. The \( \alpha \) ratio determines the contribution of each of these two components. After computing the movement amplification vector \( \mathbf{m}_a \) and extracting its corresponding hand position, we recursively applied an inverse kinematics technique (Cyclic Coordinate Descent) for estimating the angles of elbow and shoulder joints. The constant factor \( G \) was 1.4 and \( H \) was 0.7.

III. RESULTS

A. Model

We implemented a computational model of hand selection to study the potential outcome of different CIMT and RIMT therapy combinations. First, we ran simulations of 2000 trials of training in order to obtain a model of a healthy subject. Then we simulated a stroke by eliminating those neurons in motor cortex sensitive to angles corresponding to the upper right workspace (0-90 degrees) and we provided 500 additional trials of training. After neural removal the accuracy of

![Fig. 3. Results from simulations showing the probability of selecting the paretic limb (averaged within 500 trials-window), for each treatment condition after follow-up (5500 trials after stroke). X-axis indicates the ratio of directional error suppressed after execution (RIMT conditions). Y-axis indicates the ratio of treatment trials in which the use of the paretic limb was forced (CIMT conditions).](image1)

![Fig. 4. Results from simulations showing mean directional error of reaching movements executed using the paretic limb for those targets located at the affected workspace, for each treatment condition after follow-up (5500 trials after stroke). X-axis indicates the ratio of directional error suppressed after execution (RIMT conditions). Y-axis indicates the ratio of treatment trials in which the use of the paretic limb was forced (CIMT conditions).](image2)

![Fig. 5. Results from Simulations. Probability of selecting the paretic limb (left) and averaged directional error for targets appearing at the affected workspace (500 trials-window) for each of the four selected conditions: no specific therapy, CIMT, RIMT, and a combination of CIMT and RIMT protocols. Blue shadow indicates trial windows withing the treatment (3000 trials).](image3)
Fig. 6. Cortical reorganization of the left motor cortex for four simulations, after training (Healthy subject), after stroke (neural removal), and after follow-up. Each simulation corresponds with one of the four selected treatment conditions: 0.7 RIMT, 0.9 CIMT, the combination of 0.3 CIMT and 0.7 RIMT, and no specific treatment. Polar plots show the distribution of neurons in motor cortex given their preferred direction in angle bins of 30 degrees.

executed movements towards targets appearing at the upper-right workspace remains severely affected, exhibiting a mean directional error of 30 degrees, as reported in [6]. At this state, we apply two different treatments: Constraint-Induced Movement Therapy (CIMT) and Reinforcement-Induced Movement Therapy (RIMT). The first consisting in forcing the use of the paretic limb with certain probability (from 0 to 0.9), and the second consisting in the amplification of visuomotor feedback with a certain factor of help (from -0.9 to 0.9). Notice that this factor can be a positive or a negative value. Consequently, when this factor is greater than zero, visuomotor feedback is modulated to diminish directional error, while when it is smaller than zero visuomotor feedback is modulated to increase directional error. In all RIMT simulations, the amplification factor G was fixed to 0.5 (see Eq. 5), which reduced to half the movement extent (i.e. length of the movement trajectory) required to reach the target position. As a result, the model adjusted to perform shorter trajectories when using the paretic limb, and the expected energies assigned to those movements were considerably reduced.

Considering the whole spectrum of dominance for each intervention (CIMT and RIMT) we simulated the effects of 190 rehabilitation conditions (10 variations of CIMT x 19 variations of RIMT) using our model of stroke. Each therapy condition consisted in 3000 trials of training plus 2500 follow-up trials with no treatment. For each therapy condition, we examined hand selection patterns and performance in accuracy after follow-up. Results show that CIMT alone (0.9 CIMT and 0 RIMT) would promote a high probability of using the affected limb. Interestingly when both therapies are combined (0.3 CIMT and 0.7 RIMT) equal results can be achieved (Fig. 3). Improvements in motor accuracy followed a similar pattern (Fig. 4), showing that those treatments that were most effective in counteracting learned non-use did also induce the greater gains in motor accuracy. As expected, negative RIMT discouraged the use of the paretic limb, thus reducing
the frequency of exposure to directional error and hampering recovery. Similarly, maximum levels of positive RIMT compromised recovery since high reduction of error feedback impeded learning.

In order to explore the model’s dynamics along therapy and follow-up, we selected four conditions: No-therapy, pure CIMT, pure RIMT, and a combination of 30% CIMT and 70% RIMT (CIMT+RIMT). Figure 5 depicts the averaged probability of choosing the paretic limb and mean directional errors across trials (within a 500 trial-window). Results from simulations show that at the end of the treatment (i.e. trial 3000), all selected treatments crossed a threshold of performance (15 degrees of directional error), promoting spontaneous use of the paretic limb during the follow-up period. At this state the simulated stroke patients were already engaged in a virtuous cycle of recovery, which allowed for further performance improvement and restored typical hand selection patterns. Simulations for the No-therapy condition exhibited opposite effects, progressively discouraging the use of the affected limb and compromising motor performance. Interestingly, the combination of CIMT and RIMT seems to be the most effective rehabilitative approach for reestablishing standard effector selection patterns and increasing motor performance.

We explored how neural mechanisms coding the direction of planned movements reorganized after stroke and after treatment (Fig. 6). After training (simulation mimicking a healthy subject) we observe an homogeneous distribution of the cells, which cover the whole workspace of directions, showing a bias for recruiting more neurons sensitive to directions corresponding with the workspace ipsilateral to the limb (i.e. right limb). Results from simulations showed that CIMT, RIMT, and combined CIMT+RIMT, induced cortical changes by recruiting intact neurons for the codification of directions towards the affected workspace. After treatment and follow-up the distribution of neural sensitivities across the all possible input angles became closely similar to the distribution found in the simulations of a non-pathological motor cortex (i.e. healthy subject). Contrarily, the final state of the simulation for which no treatment was applied showed an atypical distribution of neural resources.

B. Clinical study

Ten chronic stroke patients were included in this preliminary analysis. Analysis of participants’ demographics revealed no significant differences between groups in any of the scores collected at baseline (Table 1).

In order to evaluate the change in hand selection patterns, we use behavioral data collected during training with the Wack-a-mole scenario. We calculate the probabilities of selecting the paretic limb averaged across weekly sessions. We normalized workspaces across subjects by mirroring target directions for those patients with their right arm affected. Results show that there was an increase in the frequency of paretic limb use only for the RIMT group (Fig. 7). Interestingly, improvements in use accumulated across the first four weeks of treatment. Contrarily, the control group showed an inverse tendency, exhibiting a lower probability of selecting the paretic limb after treatment.

Regarding results from clinical scales, one-way repeated measures analysis revealed significant improvements only for the RIMT group for the FM scale (p=0.037, Friedman test). Subjects in RIMT group showed an increase in FM of 4 ± 4.25 points after therapy and reached improvements of 12.33 ± 6.9 points at 12 weeks follow-up. Interestingly most of the gains occurred after the treatment. We did not find any other significant effects in the evolution of scores for the rest of clinical scales in any of both groups.

IV. Conclusion

In this study we presented a novel rehabilitation strategy, called Reinforcement-Induced Motor Therapy, for overcoming learned non-use and motor impairments. First, we provided a description of the implementation of a model of recovery that accounts for RIMT and CIMT procedures. Second, we described a methodology for the implementation of RIMT in VR-based setups. Third, we presented preliminary data from a longitudinal clinical study with stroke patients. Based on simulations from our model, we discuss that the combination of RIMT and CIMT protocols might be the most efficient approach for reversing learned non-use and inducing motor gains, thus providing an opportunity to curtail the intensity of CIMT protocols and overcoming its associated limitations. Results from behavioral data agree with results from simulations, and suggest that RIMT therapy may be effective in overcoming learned non-use and its beneficial effects may sustain through time.

It is important to consider the limitations of this study. In the proposed model, we greatly simplified the complexity of motor cortex and basal ganglia in favor of reducing the model’s complexity. The method we used to mimic a stroke doesn’t reflect the complexity of the pathology. We simulated hemiparesis as a lack of accuracy, and did not take into account other stroke induced impairments that would interfere with motor performance (e.g. spasticity and muscle weakness). Although results from behavioral data showed improvements in use for the RIMT group, a bigger sample would be needed to conclude whether RIMT protocols could induce sustained functional gains in real world. In addition, the effectiveness of the treatment may be strongly dependent on the patient’s profile. Further experiments should address these questions and confirm the actual impact of this new family of rehabilitation techniques.
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