

HHS Public Access

IEEE Trans Biomed Eng. Author manuscript; available in PMC 2016 June 20.

Published in final edited form as:

Author manuscript

IEEE Trans Biomed Eng. 2013 March ; 60(3): 838-844. doi:10.1109/TBME.2012.2192116.

Augmented Dynamics and Motor Exploration as Training for Stroke

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Abstract

With chronic stroke survivors (n = 30), we investigated how upper extremity training with negative viscosity affects coordination under unperturbed conditions. Subjects trained with a planar robotic interface simulating 1) negative viscosity augmented to elbow and shoulder joints; 2) negative viscosity combined with inertia; or 3) a null-field condition. Two treatment groups practiced with both force conditions (cross-over design), while a control group practiced with a null-field condition. Training (exploratory movement) and evaluations (prescribed circular movement) alternated in several phases to facilitate transfer from forces to the null field. Negative viscosity expanded exploration especially in the sagittal axis, and resulted in significant within-day improvements. Both treatment groups exhibited next day retention unobserved in the control. Our results suggest enhanced learning from forces that induce a broader range of kinematics. This study supports the use of robot-assisted training that encourages active patient involvement by preserving efferent commands for driving movement.

Index Terms

Robotic rehabilitation; skill transfer; stroke; upper extremity

I. Introduction

WHILE motor impairments due to stroke pose serious challenges to rehabilitation, robotic interfaces provide opportunities to stimulate motor learning in ways not possible with traditional therapy. Stroke survivors training with robot-applied forces can learn to straighten movement trajectories [1]. Assistive loading provided from a robot enables increases range of motion with decreased physical effort [2[]], [[]3]. While such devices facilitate access to exercise, recent investigations have shown that patients may fail to improve if not actively participating [4^{]–[}6]. Therefore, a critical goal in robotics-assisted rehabilitation is to facilitate practice while encouraging the learner to drive his/her own movement.

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Authors' photographs and biographies not available at the time of publication.

Many therapies have concentrated on teaching (sometimes enforcing) movement patterns. However, we suggest that free movement choices might better promote active involvement by the patient. Research in motor learning has shown that training on a variety of tasks provides better improvement in overall skill than repetitions of the same task [7], [8]. Active choice in which movements to practice allows the learner to focus training more effectively [9]. Even without repetition of specific movements, free movement can feature force and motion relationships that aid in general motor planning skills. Patients can direct their own training and achieve greater *agency* over their sensorimotor interactions. Such agency—the awareness of one's volitional action—arises from the fact that descending muscle commands drive limb motion as opposed to strict external control from a robot.

Rather than to enforce a given movement pattern, robotic training can stimulate motor learning by presenting robot–human interactions that augment the dynamics of the limb. Researchers have employed such environments to elicit changes in motor planning in healthy individuals, using a variety of augmentative dynamic environments, also called *force fields* [10^{],} [11]. These studies demonstrate the ability of the motor system to adopt coordination abilities specific to novel force–motion relationships. Such environments support agency since movement only occurs in response to the learner's own motor commands. To benefit rehabilitation, however, the choice of augmentative dynamics should satisfy two key objectives: to facilitate movement and to teach motor skills relevant to normal conditions outside of robotic intervention.

Movement amplification represents a type of augmentative dynamics of particular importance to motor impairment. A major advantage to such environments is allowing access to coordination training even when weakness limits voluntary motion. Researchers have used robot-applied forces to amplify human force or motion to expand the capabilities of healthy and motor impaired individuals [12[]], [[]13]. In a manner similar to error augmentation [14], movement amplification increases awareness of errors—information critical for driving adaptation. Our previous work [15] has shown that robot-applied forces can help healthy individuals learn to control novel inertial dynamics. The critical finding from this work was that improvements in performance persisted even when amplifying forces were removed.

To apply this approach to robot-assisted rehabilitation, training must support the learning of normal limb dynamics. Researchers have shown that the motor system more successfully generalizes learned motor plans between movements spanning similar positions and velocities [16], and exhibits a preference for such generalization in a joint-based coordinate frame [17]. Evidence suggests that the motor system plans according to associations between expected forces and movement states [18]. Furthermore, the motor system has been shown to transfer skills between environments with overlapping characteristics $[19]^{-[21]}$. Thus, our interest is to determine augmentative environments that stimulate learning, but also successfully support skill transfer to the arm in the absence of any external forces.

This study tested how training with movement amplifying forces and free exploration influences skill under null-field conditions. While there are many possible choices of augmentative dynamics that amplify movement, including reduction of inertial effects or

stiffness, we focus on interactions that would preserve the inertial dynamics of the arm and allow unconstrained motion. We examined three forms of augmentation: 1) negative viscosity (velocity-dependent destabilizing forces); 2) inertial combined with negative viscosity; and 3) a control with no external forces. Subjects trained with several periods of free exploration, alternating with phases of performance evaluation. To serve as an evaluation of learning, we tested subjects' abilities to perform circular movements in the absence of external forces. One possibility was that increasing the inertia of the arm would benefit coordination, though with greater effort. On the other hand, negative viscosity could stimulate greater learning through promoting broader exploration. Our findings demonstrate the exciting potential of movement amplification, particularly with negative damping, and show how the choice of augmentative dynamics has a significant impact on learning.

II. Methods

A. Human Subjects

Chronic stroke survivors (n = 30) volunteered for this study and were randomly assigned to one of three training groups. Each subject provided informed consent in accordance with the Northwestern University Institutional Review Board and was paid for their participation. Subjects trained with their affected arm (16 left-affected, 14 right-affected). Subject characteristics did not reveal significant differences between groups (according to *t*-tests), in terms of age (mean 52.0±8.2) and time since onset of stroke (mean 8.5±7.1 years). Clinical assessments, available for only some subjects (mean 20.8±9.7, upper extremity Fugl–Meyer, five per group), were insufficient to determine similarity between groups.

B. Apparatus and Implementation of Force Fields

We asked subjects to control the movement of a planar force-feedback device (see Fig. 1) as described in our previous work [22]. To focus training on the coordination of the forearm and upper arm, subjects operated the device through a wrist brace. The brace was connected to a revolute joint, such that end-point forces could be presented to the arm at the wrist. For some conditions, we programmed the device to present forces that augmented the mechanical behavior of the arm (as shown in Fig. 1), in terms of increased limb inertia of the upper arm and forearm, and/or decreased viscosity of the shoulder and elbow joints. We matched the lengths of the upper arm and forearm (L_1 and L_2) of the virtual system to those for each subject, so that virtual and real limb motions could be as close as possible.

With absolute angles of the upper arm and forearm defined as θ_1 and θ_2 , end-point forces $F_x(t)$ and $F_y(t)$ were presented according to

(1)

$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \left(J^T\right)^{-1} \left\{ M(\theta) \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{bmatrix} + B \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} + C(\dot{\theta}, \theta) \begin{bmatrix} \dot{\theta}_1^2 \\ \dot{\theta}_2^2 \end{bmatrix} \right\}$$
$$M(\theta) = \begin{bmatrix} I_1 + m_2 L_1^2 & \frac{1}{2} m_2 L_1 L_2 \cos(\theta_2 - \theta_1) \\ \frac{1}{2} m_2 L_1 L_2 \cos(\theta_2 - \theta_1) & I_2 + \frac{1}{4} m_2 L_2^2 \end{bmatrix}$$
$$C(\dot{\theta}, \theta) = \frac{1}{2} m_2 L_1 L_2 \sin(\theta_2 - \theta_1) \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$
$$B = \begin{bmatrix} b_1 & 0 \\ -b_1 & b_2 \end{bmatrix}.$$

For this study, we presented the same levels of augmented inertia ($m_1 = 1.5 \text{ kg}$, $I_1 = I_2 = 1.0 \text{ kg} \cdot \text{m}^2$) and/negative viscosity for all subjects ($b_1 = b_2 = -0.5 \text{ N} \cdot \text{m} \cdot \text{s/rad}$) during the training portions of the experiment. We set these values so that a maximum force of 15 N would not be exceeded for typical movement. This limit was based on previous studies, where we found that such levels of force interaction provided a significant learning challenge while still providing safe and comfortable interaction.

Using an overhead projector mounted on the ceiling, real-time feedback of the handle position, visual reference cues, and experiment instructions were presented on a horizontal surface overlying the planar workspace of the arm (see Fig. 1). In addition, the real-time animation included two segments approximating the motion of the forearm and upper arm. Visual reference cues included a circular reference track (shown in white, 0.1 m radius), which acted as a target path for performance evaluation, or a larger rectangular region, indicating the bounds of movement for the motor exploration portions of the experiment.

Using MATLAB XPC-Target (Natick, MA), a computer performed real-time differentiation and filtering (low-pass cut-off at 11 Hz) of the robot encoder data. Using measurements of the handle end-point position, the computer produced estimates of the subject's angular velocity and accelerations of the arm. The resulting force fields exhibited delays of less than 40 ms. Data were collected at 100 Hz. The basic rate of dynamics simulation was 2 kHz.

C. Protocol

The experiment design featured training and evaluation phases with markedly different motor activities. This separation allowed for a test of generalization and also provided subjects a contextual cue about changes in the loading from the robot. During the motor exploration phases, we instructed subjects to move the handle at their own discretion using a variety of directions, speeds, and positions within the rectangular workspace $(0.2 \times 0.6 \text{ m})$. We explained that each exploration phase should serve as preparation for the next evaluation phase. The computer signaled the user to halt motor exploration after 25 m of handle endpoint total travel.

For the performance evaluation phases, subjects were instructed to move the robotic interface quickly in four complete counter-clockwise revolutions around a target circular track (see Fig. 2). After each trial, feedback was also provided as to whether average movement speed was too fast or slow (target of 0.22 m/s). Subjects were told to achieve

accurate and smooth performance as much as possible. Four starting locations were indicated on the track. No further instruction was provided about strategy for the evaluation. For the performance evaluations, the robot presented a null field.

We presented subjects with an experiment schedule that facilitated practice for switching between training and evaluation conditions. Each session included several alternating training phases (16) and evaluation trials (160). The intervals between training phases varied between 4 and 20 trials, as shown in Fig. 3. We included different intervals of performance evaluation to test possible differences in retention. The first set of evaluation trials (20) at the beginning of the session served as the baseline from which subsequent changes in performance are compared. Each session included two 1-h blocks, with a 15-min intervening break.

Subjects performed three sessions. The first session served as a baseline condition, in which subjects trained with motor exploration and performed evaluation trials without forces (null field). The second and third sessions included either augmented negative joint viscosity or positive limb inertia and negative joint viscosity during the motor exploration training phase. Experiment groups differed in the sequence of training conditions on the second and third sessions. We will refer to these groups as NVC (Null-Field, Negative-Viscosity, Combined) and NCV (Null-Field, Combined, Negative-Viscosity), and the control group NNN (Null-Field each session), according to their sequence of training sessions. We stress that while some training phases included force interactions, all evaluation trials were in the null-field condition. Hence, this experiment tested the transfer of skills from force field to null condition. Note also that in this experiment design, the first two groups represent a "cross-over" protocol in which subjects switch to an alternate training condition after the first session (see Fig. 3).

D. Data Analysis

We devised as our main metric of performance, the *radial deviation*, or the distance between the handle and template circular track, to assess the degree of movement error. We present example trajectories of the radial deviation over time for each group (see Fig. 2). To characterize differences in learning, we analyzed changes in performance evaluations for each group. To determine the immediate impact of training, we considered changes within each session for each training condition (initial and final 20 trials). Note that this analysis does not reflect naïve transfer to novel conditions since subjects have experienced both initial exposure and evaluation trials interspersed through training. Then to determine whether the influence of training persisted, we also calculated the mean performance changes from session to session (all trials after initial evaluation). This analysis considered evaluation trials occurring in between exploration phases, and hence reflected whether subjects acclimated to the recent presence of forces interactions. We also examined success in retention by computing the change in evaluation (20 trials) in the session following exposure to force field training. We hypothesized that the training force fields would promote greater improvements in learning compared to the control. Using the metric described previously, we performed paired *t*-tests (two-tail) to assess performance changes. We compared performance between groups, using an ANOVA with two-way interactions

between three experiment factors: subject group (NCV, NVC, and NNN), session (1–3), and trial block (1–2).

In addition to comparing differences in performance during the evaluations, we wished to assess how patterns of exploration differed under each training condition. We defined the acceleration specificity as the difference in the range of acceleration (95th percentile) between sagittal and transverse axes, divided by the range of scalar acceleration. This metric ranges from entirely transverse (-1) to entirely sagittal movement (+1), where zero indicates isotropic distribution. We compared the change in specificity for each group. To account for multiple pairwise group comparisons, Bonferroni corrections were applied to *p*-values. The threshold level of significance for ANOVA and *post hoc* tests was set at a = 0.05.

III. Results

Performance in the circular movement task improved overall by session for subjects as whole (R(2144) = 0.39, MSE = 0.630, p = 1.10e-8, session main effect), while the change between blocks was not significant (R(1,9) = 0.0056, MSE = 0.00019, p = 0.94, block main effect). Groups, however, did exhibit differences (R(2144) = 3.92, MSE = 0.118, p = 2.20e-2, group main effect). Improvements in performance between initial and final evaluations differed between groups (see Fig. 4), indicating a strong influence from the form of training (R(2144) = 4.73, MSE = 0.142, p = 1.02e-2, according to the group x block interaction). No other significant factor interactions were found. Movement speeds were similar between groups (grand mean: 19.9 ± 8.7 , mm/s, *t*-test, p>0.6). A check of initial performance prior to training also revealed no significant differences between groups (grand mean: 6.3 ± 2.7 , mm radial deviation, *t*-test, p>0.3). To probe group differences further, we next examine the within day changes in performance in terms of pair-wise group comparisons.

Within-day changes

Analysis of within-day changes in performance (initial and final 20 evaluation trials) revealed the most dramatic error reductions from training with negative viscosity. In session 1, subjects exhibited trends of gradual improvement (null-field training) that did not achieve significance. In contrast, in session 2 training with negative viscosity resulted in a mean reduction of 1.5 mm (CI: 0.2, 2.9) in radial deviation (mean change 16.8%; CI: 27.5, 6.21, p = 5.90e-3, paired *t*-test). In between-group comparisons, for session 2 training with negative viscosity resulted in greater reduction in error compared with the combined condition (mean difference 27.4%, CI: 11.5, 46.7; p = 8.3e-3, *t*-test). In session 3, the NCV group (training with negative viscosity) exhibited a 0.9 mm (CI: -0.1, 1.9) increase in radial deviation within the session (mean change 17.7%; CI: 20, 33.3, p = 3.12e-2, paired *t*-test), indicating possible fatigue effects or interference from prior learning (training with combined).

Session-to-session changes

While the immediate impact of training can be seen with within-session changes, it is important to consider whether improvements persist over the course of days. In terms of changes between sessions, training with destabilizing forces promoted significant improvements that persisted into last session. In session 2, combined training resulted in an

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average of 1.1 mm (CI: 0.1, 2.1) decrease in radial error (mean 13.7, CI: 1.7, 25.7% change relative to session 1, p = 3.44e-5, paired *t*-test). Similarly, in session 2, negative viscosity training resulted in an average of 1.9 mm (CI: 1.0, 2.7) decrease in radial error (22.4%; CI: 15.7, 19.1 change relative session 1, p = 3.44e-5, paired *t*-test). Results remained significant only for each of the test groups (NCV and NVC). In terms of between-group comparisons, for session 2 training with negative viscosity resulted in greater reduction in error compared with the control condition (mean difference 13.2%, CI: 23.1, 3.2; p = 1.23e-2, *t*-test).

Next session retention

We examined the evaluation trials at the beginning of each session, and found that only test groups retained performance improvements when evaluated in the session after their exposure to the force fields. Combined training (NCV group) resulted a mean of 1.1 mm (CI: 0, 2.16) reduction in radial deviation (15.6%; CI: 2.54, 28.7 change relative session 1, p = 2.44e-2, paired *t*-test). Negative viscosity (NVC group) training resulted a mean of (1.4 mm CI: 0.2, 3.0) reduction in radial deviation (18.7%; CI: 3.1, 34.2 change relative to session 1, p = 2.37e-2, paired *t*-test). The control group did not exhibit significant retention, with only a 0.7 mm (CI: -0.4, 1.8) reduction (9.8% mean reduction; CI: -4.1, 23.6).

Direct effect of force fields

We examined handle motion during motor exploration and found that negative viscosity exhibited the strongest impact on expanding the distribution of movement. As shown in the histograms of acceleration in Fig. 5 (session 2), training with negative viscosity resulted in increased accelerations especially in the sagittal axis of motion (relative to baseline training). With negative viscosity training, the specificity of acceleration in the sagittal axis increased significantly (0.13 mean increase; CI: 0.078, 0.19, p = 3.21e-4) and was greater than the control (0.13 mean difference; CI: 0.038, 0.22, p = 3.17e-2). Similar results were observed in terms of the specificity of velocity. Combined training exhibited a trend of a shift in activity from the transverse to the sagittal axis (see Fig. 5, session 2, row 1), though this effect was not significant. This distribution analysis suggests that encouraging practice with elbow flexion–extension can aid skill transfer to the null-field condition.

IV. Discussion

This study examined how destabilizing forces affect arm coordination in stroke survivors. We presented training in the form of free motor exploration and then tested the ability to perform circular movements in the absence of external forces. We compared two forms of force fields and found that both negative viscosity and combined field training exhibited lasting benefits by the final short-term retention test. However, we observed the most dramatic within-day improvement for negative viscosity training. Analysis of the distribution of acceleration states during motor exploration demonstrated that training with negative viscosity increased activity in the sagittal axis of motion. This analysis of movement distribution suggests that expanding exploration in neglected movement patterns benefits recovery of motor coordination.

Robot-applied forces have clear utility for augmenting human capabilities [12[]], [13], yet the means to encourage active involvement from the learner has been unclear. Recent work in robot-assisted rehabilitation has shown benefits from assisting the patient as needed [23] and employing performance-based changes in difficulty [24[]], [26]. While robotic devices can facilitate access to exercise, recent investigations have shown that patients fail to improve when participating in passive movement [5[]], [6[]], [26]. As with applying EMG-dependent forces [27], our experiment conditions featured forces that enabled more movement while not sacrificing active involvement from the learner.

Our findings establish a potential key role for robotics in rehabilitation by demonstrating successful skill transfer from training with forces to unassisted movement. It was plausible that the motor system would reject learning of force fields, or even retain learning that was incompatible with evaluation conditions. Evidence suggests that manual training with one type of sensorimotor mapping can interfere with learning under subsequent conditions [28], [29]. The human motor system has demonstrated skill transfer between environments with overlapping characteristics [19], [20]. We did in fact observe increased error for the NCV group in session 3, which might indicate a competition of strategies between force fields. While external forces must introduce a different sensorimotor environment, we designed force fields to mirror features of the unaided arm. The motor system has been found to prefer a joint-based coordinate system when learning a novel environment [17]. We presented force interactions that were in the same joint coordinates system as the arm, potentially easing the transition from training to evaluation conditions. However, the issue of the relative benefits of training with joint- or Cartesian-based force fields deserves further study. Furthermore, other environments that encourage movement should be investigated and compared those used in this study.

Motor exploration could serve to improve formation of neural representations. In contrast to refining performance for predefined movements, broad experience of movement states might facilitate learning via improved representation of limb dynamics, analogous to identification of engineering systems [30]. Interestingly, we observed increased error when subjects initially switched from motor exploration to task performance (session 1), which suggests an initial disruption to the iterative error-correction processes. For motor recovery, training on a variety of tasks provides better improvement in overall function than repetitions of the same task [7], [8]. Rather than rote memorization of motor commands, the nervous system appears to learn associations between forces and movement states [18]. Allowing free movement presumably would provide the richest experiences of these dynamic relationships.

Another interpretation of the learning observed in this study is that the destabilizing forces altered preferred movement patterns. A pivotal finding in stroke rehabilitation is that forced use reverses the impact of "learned nonuse" of the affected limb [31], [32]. This study extends this concept to patterns of movement within the affected limb. Just as mechanical characteristics of the arm and wielded objects influence preferred movements in goal directed tasks [33^{], [34]}, the typical patterns of free exploration naturally differ with external loading. Researchers found that infants, in learning to express reaching, exhibited exploratory actions subject to intrinsic dynamics of the arm [35^{], [36]}.

Practice in neglected patterns of movement could have benefitted the motor system through use-dependent learning [37]. Force fields can break stereotypic patterns of movement, thus enabling exposure to a larger range of experiences. Our analysis of the distribution of movements (see Fig. 5) suggests that motor exploration training for stroke survivors expanded the range of movements, particularly in the direction of elbow flexion–extension. Such analysis could allow more detailed characterization of movement biases in stroke survivors and help individualize training goals.

Finally, this study provides important foundations for new avenues in robotic-assisted therapy. Our approach offers tools to address a key challenge in rehabilitation—increasing accessibility to movement training while maintaining active involvement of the learner. We have extended the findings of our earlier study on healthy subjects, which showed that negative viscosity can improve learning of novel inertial force fields. Because this study did not control for clinical assessment levels of subjects, it is unclear how the effectiveness of such training might depend on the severity or specific motor deficit. More work is needed to determine how such force interaction should be customized according to individual patient needs, or whether changing levels of negative viscosity can induce greater learning. While it remains to be seen whether training with such destabilizing forces might also transfer to improved ability in activities of daily living, the current results show clear benefits to training not found with repetitive practice alone.

Acknowledgments

This work was supported by National Institutes of Health under Grant NS053606 and Grant T32 HD07418.

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Fig. 1.

(a) Robotic interface interfaced to the arm about a free pivot at the wrist. Subjects were allowed to freely interact with each load in a "motor exploration" stage. Following exploration, subjects made counterclockwise circular movements during task performance trials at random starting locations of a 0.1-m radius circular track. (b) Virtual arm augmented the existing dynamics of the human arm with negative viscosity in the elbow and shoulder and/or positive inertia to the upper and forearm, delivering end-point forces to the arm at the wrist.



Fig. 2.

Trajectories of the initial evaluation (four sample trials) show typical improvement over the course of three sessions (typical NVC subject). Color gradation (upper plots) indicates variations between highest and lowest speeds observed (red to blue). Mean radial deviation (blue line, lower plots) indicate reduction of systematic error.



Fig. 3.

Average radial deviation for three groups decreased markedly in the first session (eight trials moving average shown) and showed abrupt increases following exposure to periods free exploration training (blue dashed). Groups (rows) differed in the sequence of training fields for each session (columns): negative viscosity, combined load, null field. Note that all evaluation trials are under null-field conditions.



Fig. 4.

(a) In within-day changes for session 2 (initial and final 20 trials, left), only training with negative viscosity reduced radial deviation (mean change 16.8%; CI: 27.5, 6.21, p = 5.90e-3, paired *t*-test). Negative viscosity training resulted in greater error reduction compared with the combined condition (mean difference 27.4%, CI: 11.5, 46.7; p = 8.3e-3, *t*-test). (b) Session to session (center), decreased radial deviation was observed for combined (session 2: mean 13.7, CI: 1.7, 25.7% change, p = 2.95e-2, paired *t*-test) and negative viscosity training (session 2: 22.4%; CI: 15.7, 19.1, p = 3.44e-5, paired *t*-test). (c) Following the second session, both test groups exhibited retention of improvements (right), for combined training (15.6%; CI: 2.54, 28.7, p = 2.44e-2, paired *t*-test) and negative viscosity training (18.7%; CI: 3.1, 34.2, p = 2.37e-2, paired *t*-test).



Fig. 5.

Histograms of the handle acceleration in plane (group averaged, 50 point bins) show how training force fields (center and right) differ from baseline distributions (left). Negative viscosity training exhibits trends of increasing activity in the sagittal axis (note greater red coloration along the vertical), while combined load tends to decrease large accelerations overall (+/o signs indicate increase/decrease where 95% CI intervals exclude zero). These findings suggest that negative viscosity facilitates greater elbow flexion–extension activity during motor exploration training.