Negative viscosity can enhance learning of inertial dynamics.

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***Abstract*—We investigated how learning of inertial load manipulation is influenced by movement amplification with negative viscosity. Using a force-feedback device, subjects trained on anisotropic loads (5 orientations) with free movements in one of three conditions (inertia only, negative viscosity only, or combined), prior to common evaluation conditions (prescribed circular pattern with inertia only). Training with Combined-Load resulted in lower error (6.89±3.25%) compared to Inertia-Only (8.40±4.32%) and Viscosity-Only (8.17±4.13%) according to radial deviation analysis (% of trial mean radius). Combined-Load and Inertia-Only groups exhibited similar unexpected no-load trials (8.38±4.31% versus 8.91±4.70% of trial mean radius), which suggests comparable low-impedance strategies. These findings are remarkable since negative viscosity, only available during training, evidently enhanced learning when combined with inertia. Modeling analysis suggests that a feedforward after-effect of negative viscosity cannot predict such performance gains. Instead, results from Combined-Load training are consistent with greater feedforward inertia compensation along with a small increase in impedance control. The capability of the nervous system to generalize learning from negative viscosity suggests an intriguing new method for enhancing sensorimotor adaptation.**

I. Introduction

THE influence of humans-machine interaction in motor learning offers exciting new prospects for the retraining of skills after neural injury. One promising form of such interaction is movement amplification from robotic assistance[1]-[2], though learning and generalization of motor skills under these conditions is not yet well understood. While typical loading from positive impedances such as weights or elastic bands can provide resistance to movement and promote strengthening, negative impedances arise only from an active agent such as a therapist or a robotic interface. For individuals with motor impairment, negative impedance could reduce workload while providing sensory-motor re-training. For healthy individuals, force fields presented during robotic training have already demonstrated dramatic adaptation in manual coordination with relatively brief exercise [3]-[4]. The challenge with any training paradigm, however, is whether the individual can both learn and generalize learning to unpracticed conditions.

The critical question in employing movement amplification in manual training is whether any potential benefits will be corrupted by inappropriate learning. One plausible outcome of training with the negative viscosity is that the motor system would adopt a feedforward strategy specific to negative viscosity and then fail to transition to normal conditions. Another alternative is that destabilizing effects of negative viscosity leads to excessive stiffening via co-contraction and hence poor learning and a frustrating level of exertion on the part of the subject. On the other hand, the motor system might be capable of decomposition of the elements present in training, so that a useful representation of the environment to be learned can be extracted while that of the negative viscosity suppressed. Experimental catch trials, where the forces are unexpectedly changed, can often reveal the feedforward component of the control. Still another possibility is that negative viscosity may actually lead to enhanced learning, since broader exploration might promote a more complete representation of the environment.

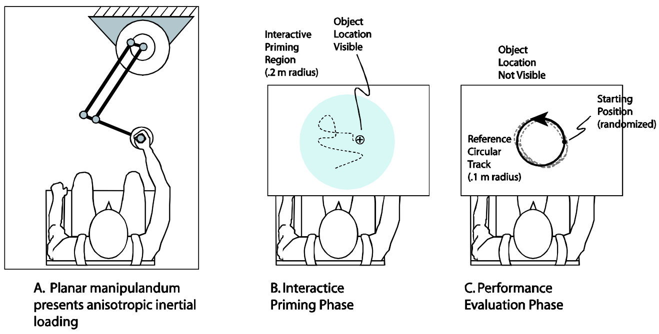

Fig. 1 (A) We simulated various anisotropic inertial loads with a force-feedback planar manipulandum. (B) Subjects were allowed to freely interact with each load in a "free exploration" stage. Feedback of the cursor position was available for each free exploration stage. (C) Following exploration, subjects made counter-clockwise circular movements with the manipulandum during an task performance trials at random starting locations of a 0.1 m radius circular track. Feedback of the cursor position was omitted during the Main Treatment trial blocks.

Dynamic computer models of the assumed biomechanics, control and learning have often able to further reveal components of the control [3]. They can offer suggestions of how the nervous system might accomplish the behavior seen in the experiment. Moreover, because the evaluation task in the present experiment is cyclic, we can employ new analysis that investigates the phase lead or lag in the system to elucidate more information on control strategies. Stiffness, damping, and feedforward control each depend on errors differently and have a unique phase.

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We conducted a preliminary investigation into how learning an inertial load might be supplemented with active impedance (negative viscosity). We examined how a period of training with both negative viscosity and inertia can benefit performance when the viscosity is removed and only the inertial load remains. We compared the effectiveness of this training to training with an inertial load alone, and also compared it with training with negative viscosity training alone. Finally, we employ a novel modeling analysis of the dynamics that examines movement error in terms of magnitude and phase. Our findings demonstrate that exploratory training with negative viscosity improves learning and generalization by promoting broader exploration during training and developing controls during training that can be effectively used to perform better in the final evaluation. This suggests an intriguing new approach for machine-facilitated learning that may impact training areas such as sports, piloting, teleoperation, and therapy.

II. METHODS

A. Humans Subjects

In this study 26 healthy individuals volunteered and were randomly assigned to either the *Inertia-Only* or *Combined-Load* subject groups. We later included a third group with 13 healthy individuals participated as a part of the *Viscosity-Only*. All participants reported have normal or corrected to normal vision. Each subject provided informed consent in accordance with Northwestern University Institutional Review Board. Individuals were not paid for their participation. Two subjects reported being left handed. Subjects performed the task with their dominant arm.

B. Apparatus and Implementation of Anisotropic Loads

We asked subjects to control the movement of a two-degree of freedom planar force-feedback device (Fig. 1) described elsewhere [5]. We programmed the device to present forces representing an object with unfamiliar mechanical behavior: anisotropic inertial loading and/or negative viscosity. We chose such loading conditions to mimic the inherent anisotropy of the arm [6], yet posed an unfamiliar and challenging motor task to learn. During the task, the handle responded as if it were a physical mass along one axis, while no load was present in the perpendicular axis. In some cases, we included anisotropic negative viscosity loads aligned with the axis of the inertial load. We selected five orientations for the anisotropic loads: θ_m=0, 36, 72, 108, 144 degrees with respect to the frontal plane. End-point forces $F_x(t)$ and $F_y(t)$ approximating inertial and viscous loads were presented according to:

$$\begin{bmatrix} F_x(t) \\ F_y(t) \end{bmatrix} = R^t \begin{bmatrix} 0 & 0 \\ 0 & m \end{bmatrix} R \begin{bmatrix} \ddot{x}(t) \\ \ddot{y}(t) \end{bmatrix} + R^t \begin{bmatrix} 0 & 0 \\ 0 & b \end{bmatrix} R \begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \end{bmatrix},$$

$$\text{where } R = \begin{bmatrix} \cos\theta_m & \sin\theta_m \\ -\sin\theta_m & \cos\theta_m \end{bmatrix}. \quad (1)$$

We chose a mass parameter *m* of 0 or 3 kg and a viscosity parameter *b* of either 0 or -10 N-s/m. With the rotation matrix R, various anisotropic loads were selected representing orientations of load. Using MATLAB XPC-Target (Natick, MA) a computer performed real-time differentiation and filtering (fourth order, low-pass cut-off at 11 Hz) of the robot joint-angle encoder data and calculated estimates of the velocity and acceleration of the handle end-point. Data were collected at 100 Hz. The basic rate of dynamics simulation was 2 kHz.

Subjects were asked to perform two tasks using the robotic manipulandum: (1) training with free exploratory movements (*free exploration*) followed by (2) performance of a prescribed circular movement (*performance evaluation).* During free exploration, subjects were instructed to move the object at their discretion using various directions, speeds, and positions within a circular region (0.1 m radius centered within the workspace). Subjects were told that the exploration stage (1) would feature an environment similar to that experienced during the subsequent evaluation stage (2), but could have missing or added elements. The computer signaled the user to halt free exploration after 15 meters of handle endpoint total travel. Using an overhead projector, visual feedback of the handle-object position and the circular interaction region as presented on a tabletop covering the planar workspace. The experiment groups differed in terms of the loading conditions presented during free exploration. The *Viscosity-Only* training group was presented with no external inertial loading and a viscosity term was set to -10 N*s/m. The *Inertia-Only* training group was presented with no external viscous loading while the inertial term was set to 3 kg. The "*Combined-Load* exploration" was presented with both negative viscosity and inertial loading during exploration. During performance evaluation (2), subjects were instructed to move the robotic interface in three complete counter-clockwise revolutions at about 1 revolution per second. Subjects were told to achieve accurate and smooth performance as much as possible in circular movements about a target track (0.1 m radius). During normal trials, the performance evaluation included the same inertial load as that presented during the free exploration stage. However, the viscosity term (Eq-1) was set to zero during performance for all trials. In some instances, *catch trials* were presented, in which the loading conditions were covertly changed with respect to those presented during free exploration. Random starting locations were indicated on the circular track at $\pi/8$ intervals.

Subjects were presented first with *Pre-Adaptation Treatment* sequence followed by a *Main Treatment* sequence. For each treatment, a series of experiment blocks were presented in which free exploration was followed by a sequence of task performance trials. A brief break (~3 minutes) was provided between treatments. In the *Baseline* Treatment, subjects were presented with a set of trials in which no load was presented and visual feedback of the handle endpoint was available for both free exploration and task performance stages. The *Baseline* Treatment first presents 3 blocks, a free exploration stage, and 12 task performance trials. Visual feedback was available only during free exploration. Each of the last two blocks of the *Baseline Treatment consisted of* a free exploration stage, 10 task performance trials and 2 *Initial Exposure* catch trials> Initial Exposure catch trials introduced unexpected loads (either θ_m= 72 or 144 degrees). Each *Main Treatment* sequence consisted of 5 blocks, each in turn associated with a different anisotropic load, a free exploration stage, 10 performance evaluation trials and 2 no-load catch trials—trials in which the load was unexpectedly absent. Similar to the *Baseline* sequence, visual feedback was available only during free exploration. Presentation of the no-load catch trials allowed the analysis how free exploration influenced subjects' ability to adopt a feedforward strategy specific to each object.

C. Modeling Predictions.

Researchers have found evidence for the structure of control schemes by evaluating generalization between environments, and by analyzing responses unexpected load changes. For the special case of sustained rhythmic arm movement, we show how elements of feedforward compensation and impedance control can be revealed by analyzing *phase* trends as well as the more commonly inspected changes in magnitude. We present a simple model based on 'feedforward control and computed torque control described by Spong et al., (2005, see Ch. 6.4) [7]. We use this model to describe how the human motor scheme might use impedance and/or feedforward control elements to compensate for a load. While we only depict parameter values at a few levels for each parameter, these examples demonstrate the general influence of each control element. We will use this model to compare how well candidate control schemes explain performance trends observed in this study.

Consider a standard control system schematic with plant *G(s)*, feedback controller *C(s)*, and feedforward controller $\hat{G}(s)^{-1}$. Rather than representing the complete arm and object dynamics, this feedback system describes the effective dynamic behavior at the endpoint. Let us assume the endpoint impedance can be approximated as a simple inertial and viscous load, so that $G(s) = (ms^2 + bs)^{-1}$. This term can include physical (e.g. biomechanical and machine interface) and virtual environment elements. The feedforward controller $\hat{G}(s)^{-1}$ on the other hand represents expectations that may differ from actual conditions with an expected inertia $\hat{m}$ and viscosity $\hat{b}$, so that $\hat{G}(s) = (\hat{m}s^2 + \hat{b}s)^{-1}$. The impedance control term *C(s)* can represent online disturbance rejection, due to co-contraction or online error correction, and can be parameterized by proportional and derivative gains according to $C(s) = K_p + K_d s$. The total error transfer function $G_e(s)$ between the error and intended movement can then be expressed as:

$$G_e(s) = \frac{e(s)}{r(s)} = \frac{(m-\hat{m})s^2+(b-\hat{b})}{ms^2+(b+K_d)s+K_p} \qquad (2)$$

From the above expression, it can be shown that a particular error magnitude and phase arises from a given set of physical and control scheme parameters and operating frequency. One possible means to reduce error due to external load is to employ feedforward control so that and the expected inertia and viscosity agree with the actual values. Alternatively, feedback control alone can recover performance as impedance control increases, i.e.with larger K_p and K_d.

This model can also elucidate the contribution of feedforward control from examination of catch trial conditions (where external load is unexpectedly removed for a single movement). According to Equation-2, employing only impedance control ($\hat{m} = 0, \hat{b} = 0$), would result in negligible error during catch trials. Alternatively, relatively low impedance control along with a feedforward model of inertia would result in prominent cyclic errors during catch trials. Improved compensation of the inertial load would yield reduced error during normal trials and increased error in catch trials, while relatively high impedance control would result in reduced error in both normal and catch trials. The expressions above can be used to detect specifically whether a feedforward model of viscosity or inertia is present. Note that since the inertial and viscous terms in the numerator of Equation 2 are of different order, any discrepancy between the expected viscosity $\hat{b}$ and the actual viscosity b should result in increased error magnitude for both normal and catch trials. In addition, the presence of a feedforward model of viscosity would cause increased phase lag in the error signal with respect to the intended motion. Thus, this model suggests that a feedforward scheme that includes false expectation of viscosity cannot mask error in mass compensation.

III. Results

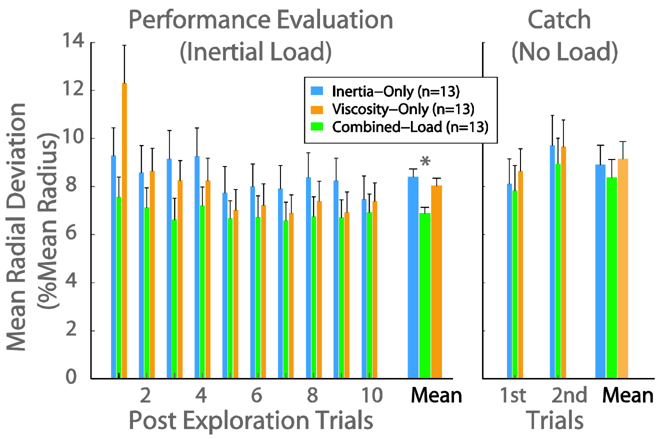
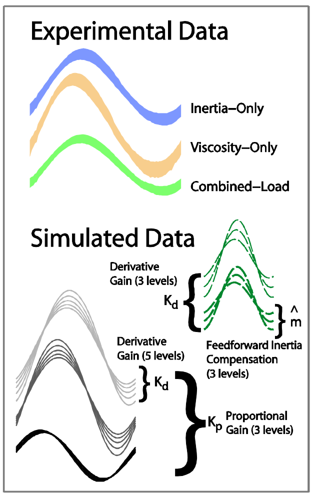


Fig. 2 (Left) The *Combined-Load* (inertia and negative viscosity) training group made circular movements with overall lowest average radial error deviation compared to the *Inertia-Only* and *Viscosity-Only* training groups (post-hoc Tukey's HSD, p=1.56e-6 and p=1.87e-9). High first trial error with *Viscosity-Only* suggests feedforward strategy incompatible with inertial loading. (Right) Analysis of no-load catch trials (five load conditions) indicates similar low impedance strategies between *Inertia-Only* and *Combined-Load* training groups, with increased error between first and second trials. Higher catch trial error from *Viscosity-Only* suggests a control scheme that is also incompatible with no load conditions. Error bars represent 95% CI across all trials.

Subjects from each group typically exhibited adaptation to changes in inertial loading, though systematic errors persisted indicating incomplete learning. Analysis of the average radial deviation revealed significant effects from experiment factors in Evaluation and Catch trials. Results from ANOVA of Evaluation trials indicated influences from each experiment factor: subject group (F[2, 1800] = 28.57, MSE = 0.04037, p= 6.12e-13), load type (F[4, 1800] = 9.91, MSE = 0.01401, p=6.2e-8), and trial sequence (F[9, 1800] = 8.81, MSE = 0.01245, p=4.5e-13). Interactions were significant for the group-by-load effect (F[8, 1800] = 5.15, MSE = 0.00728, p=2.3e-6) and the group-by-trial effect (F[18, 1800] = 2.88, MSE = 0.00408, p=4.6e-3). These findings indicate that load orientations differed in difficulty, and some performance changes occurred over the course of performance trials following free exploration, though these effects depended on subject group. In contrast, results from ANOVA for catch trials indicated a strong influence only for effects from load type (F[4, 368] = 20.0, MSE = 0.0318, p=6.4e-14) and trial sequence (F[1, 368] = 9.5, MSE = 0.1511, p=2.2e-3). Interactions were not significant for catch trials. These results suggest that subject groups had similar sensitivity to unexpected loads, and that this sensitivity decreases after the first catch trial.

Our main observation of group differences is that including free exploration with combined inertia and negative viscosity resulted in lowest overall error. According to the mean radial deviation metric (% of mean trial radius), the *Combined-Load* training group exhibited 18.0% lower error (6.89±3.25, mean and SD) compared to *Inertia-Only* (8.40±4.32, mean and SD) and 14.2% lower compared to *Viscosity-Only* (8.03±4.13, mean and SD). According to Tukey HSD post-hoc tests, these differences were significant for Combined-Load compared to Inertia-Only (1.51; CI:1.00, 2.02; p=5.0e-11) and compared to the Viscosity-Only group (1.14; CI: 0.62, 1.65; p=5.4e-7). Differences between Viscosity-Only and Inertia-Only were not significant (0.37; CI: 0.14, 0.88; p=0.20). While we observed performance differences between groups in Evaluation trials, ANOVA did not reveal differences between groups in terms of catch (no load) trials. The *Combined-Load* training group exhibited an average radial deviation (% of mean trial radius) of 8.38±4.31 group mean, compared to 8.91±4.70 from *Inertia-Only* and 9.14±4.17 from *Viscosity-Only*.

Comparisons of experimental error trajectories with simulated responses from our model (See *Modeling Predictions* section) suggests that *Combined-Load* and *Inertia-Only* training groups employed control schemes incorporating both feedforward and impedance control. While responses from a model including impedance control alone (see Fig. 4A) roughly match amplitude and phase of Evaluation trials, they fail to fit catch-trial behavior for any choice of impedance control parameters. However, for *Combined-Load* and *Inertia-Only* training, including a simple feedforward model of inertia in the simulation yields trajectories that conform to both trial conditions (see Fig. 4B). In terms of the simple control schemes we consider in our modeling analysis, the observed radial deviation trajectories are consistent only with control including impedance control with partial feedforward inertial compensation. Note that these results are only apparent when we consider the magnitude and phase from both Evaluation and Catch trials.



Simulation Parameter Values

Feedforward Control (FF)		Impedance Control (IC)	
Inertia, $\hat{m}$ (%Training Load)	Viscosity, $\hat{b}$	Prop., K_p (N/m)	Deriv., K_p (N-s/m)
A. Impedance Control Variation Only			
0	0	30, 200, 600	35, 40, 45, 50, 55
B. FF Inertia , IC Variation			
45	0	30, 200, 600	35, 40, 45, 50, 55
C. FF Inertia & Negative Viscosity, IC Variation			
45	100	30, 200, 600	35, 40, 45, 50, 55
D. FF Inertia Variation, IC Variation			
25, 45, 55	0	30	40, 50
Loading: Inertia, 3 kg; Viscosity, -10 N-s/m			

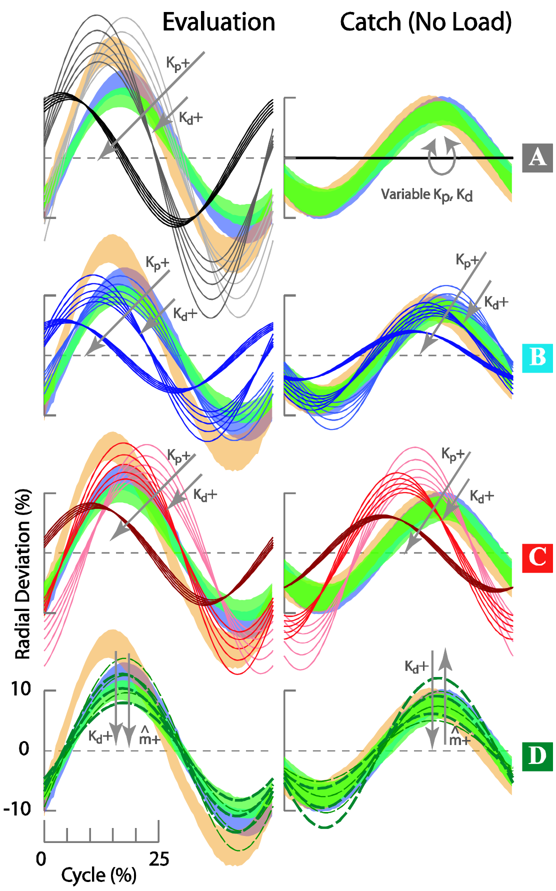


Fig. 3 Radial deviation time-series (ensemble average 95% CI shown) for the first Evaluation and Catch trials following free exploration from experimental and simulated data from various candidate control scheme (by rows) are shown (fixed scheme per row). Numerical values for feedforward (3 levels $\hat{m}$) and impedance (5 levels K_d, 3 levels K_p,) control parameters for each proposed scheme (below, left) are shown. Schemes combining impedance control and a feedforward model of inertia **(B)** show agreement with Evaluation and Catch trial trends much better than impedance control **(A)** alone. Impedance control up-regulation does not explain differences between *Combined-Load* and *Inertia-Only* training groups, since errors differed during Evaluation but not Catch trial conditions. Including a feedforward model of negative viscosity **(C)** tends to increase radial deviation and phase shifts—trends not evident with *Combined-Load* training. An increase in feedforward inertial compensation combined with greater impedance (K_d only shown) control **(D)**, however, can reproduce trends of decreased error in Evaluation with without differences in Catch trials. Impedance control differences alone could explain error increases and phase shifts by the *Viscosity-Only* group, though a feedforward model of viscosity might contribute.

The assumption of constant control schemes between Evaluation and Catch trials, however, fails to predict the performance by the *Viscosity-Only* training group (See Fig 3C). Large cyclic errors exhibited by the *Viscosity-Only group* suggests that the learning that was inappropriate for Evaluation conditions. Subjects of the *Viscosity-Only* group evidently altered their strategies after the first trial post exploration to accommodate the presence of inertial loading. Radial deviation trajectories suggest that the *Viscosity-Only* group initially employed either an impedance control strategy alone (See Fig. 3A) and/or feedforward model of negative viscosity (See Fig. 3C). Because inertia was the only loading during task performance, the presence of a feedforward model of negative viscosity would have increased error amplitude for both Evaluation and Catch trials (See Fig. 3C). In addition, such a scheme would cause characteristic increases in phase lag in Evaluation trials, and phase lead in Catch trials. These trends suggests that that The *Viscosity-Only* training group quickly adopted a feedforward model of inertia during performance trials, while any feedforward model of negative viscosity was rapidly abolished.

Changes in impedance control alone cannot readily explain differences between the *Combined-Load* exploration and *Inertia-Only* groups. One possible outcome of training with negative viscosity is an increase in vigilance enabling more efficient responses to unexpected load conditions. As shown in Figure 3, training with the *Combined-Load* condition resulted in the lowest amplitude radial deviation in Evaluation trials—a pattern which by itself could indicate greater impedance control or improved feedforward compensation. However, catch (no load) trial results indicate similar increases in error for both *Combined-Load* and *Inertia-Only* training groups, which suggests that these groups developed comparable feedforward strategies. Because catch trial analysis indicates no discernable difference between the *Combined-Load* exploration and *Inertia-Only* groups, some compensation strategy at work other than impedance control.

Our analysis indicates that the *Combined-Load* training group adapted to inertial loads as well if not better than the *Inertia-Only* training group. In contrast to *Viscosity-Only*, the *Combined-Load* training group did not exhibit large errors in the initial trials post exploration, nor any noticeable shift in radial deviation phase. Instead *Combined-Load* training resulted in very similar radial deviation trajectories with respect to *Inertia-Only* (see Fig 3.), except with lower amplitude during Evaluation. One possible explanation is that subjects who trained in the *Combined-Load* condition acquired improved feedforward inertia compensation and adopted a small increase in impedance control (See Fig. 3D). Specifically, our modeling analysis indicates that greater dissipation (derivative gain K_d) might contribute some reduction in radial deviation amplitude in both Evaluation and Catch trials, while increased inertia compensation would have opposite effects between trial types.

A comparison of mean speed and endpoint force data observed during the exploration stages indicate greatest activity from the *Combined-Load* group. Using Tukey's post-hoc tests for significant differences, we found that the average speed was 12.0% larger for the *Combined-Load* group compared to the *Inertia-Only* group (0.036 m/s; CI: 0.002, -0.070; p=0.038), but was 18.8% smaller with respect to the *Viscosity-Only* group (-0.077 m/s; CI: -0.111, -0.042; p=8.37e-7). The *Inertia-Only* group also exhibited 37.9% smaller average speed compared to the *Viscosity-Only* group (0.112 m/s; CI: 0.078, 0.147; p=1.24e-12). In contrast to the trends in speed, we found that the average force was largest for the *Combined-Load* training group: 22.9% greater compared to the *Inertia-Only* group (1.27 N; CI: 0.42, 2.11; p=7.99e-15) and 179.0% greater compared to the *Viscosity-Only* training group (4.36 N; CI: 3.51, 5.20; p=1.46e-3). The *Viscosity-Only* group exhibited 55.9% smaller average force compared to the *Inertia-Only* group (-3.09 N; CI: -3.94, -2.25; p=4.24e-14). These trends suggest a greater similarity in training for the two groups that experience inertial loading during free exploration, with a somewhat increased range of exploration for the *Combined-Load* training group.

IV. Discussion

Our findings demonstrate that training with negative viscosity can improve learning of a passive object manipulation task, achieving even better performance than training with the passive conditions alone. These findings suggest a two-part process of learning through enhanced sensorimotor experiences and successful generalization between mechanical environments. Our analysis suggests that negative viscosity alters the efficiency of internal model formation of inertial loading by promoting broader exploration during training. We argue then that the motor system is able to transfer the enhanced motor scheme to the passive environment by relating the shared features between environments. These findings offer an intriguing new method for facilitating sensorimotor adaptation through augmentation with negative impedance.

Our results provide an example of skill transfer between environments that differ sharply in mechanical behavior. One possible outcome of training with the negative viscosity would be an after-effect from feedforward control that degrades performance in the evaluation stage (see *Modeling Analysis* section). Performance by the *Viscosity-Only* group indicated initial large errors Evaluation, which suggests a significant conflict between the strategies learned during training and that of performance conditions. While the *Viscosity-Only* group perhaps learned appropriate information about the anisotropy of loading, other aspects of their experience was not applicable to controlling the inertial loads. However, training with combined inertia and negative viscosity led to superior performance (34.8% versus 5.78% reduction in average radial deviation) compared to the *Inertia-Only* condition. Rather than interfering with learning, training with combined negative viscosity and inertia may have promoted learning with enhanced compatibility with evaluation conditions.

Analysis of catch trials suggests that training with combined inertia and negative viscosity preserves low impedance control appropriate for controlling the isolated inertial loads. One possible effect of training with negative viscosity is an enhancement of impedance control, for example by higher co-contraction or feedback gains of disturbance rejection scheme. However, analysis of average radial deviation suggests that the *Combined-Load* training group exhibited catch trial error comparable to the *Inertia-Only* group (see Fig 2, 8.348±4.31% versus 8.91±4.70%). It is likely that training with negative viscosity induced an increase of attention. However, only training in the *Combined-Load* conditions provided an enhancement of sensorimotor experiences relevant to inertial loading. One possibility is that subjects of the *Combined-Load* exploration acquired both an improved model of inertia and increased impedance control. Combined impedance-based and feedforward control [8] would achieve better performance under normal loading and be more robust to catch conditions.

Beyond preserving the formation of a feedforward scheme, we argue that including negative impedances can strengthen the learning of passive loading. Negative viscosity effectively introduces a form of error augmentation since it amplifies intended movements. Enhanced or augmentative feedback [9]-[10] presumably facilitates learning by strengthening the associations between motor actions and sensory consequences, for example as in the use of sensory augmentation [11]. In contrast to perceptual changes, however, altering the force-motion sensitivity through mechanics necessitates changes in the energetic requirements and stability—important factors in promoting motor adaptation. Inertial characteristics of objects and the arm evidently influence preferred movements [12]. Schaal et al. (1996) [13] noted that in ball bouncing, the human motor system autonomously adjusts control towards a stable strategy. In these cases, the sensitivity of movement to motor input can be attributed to the impedance at the interface between the arm and environment, which will clearly influence how easily sensory-motor associations are learned.

Enhancing motor learning by including negative impedances could have important implications to rehabilitation and other motor skill training endeavors. Loads that amplify movement are especially important for individuals with motor impairment who have limited movement capabilities [14]-[15]. The current study demonstrates the capacity of the motor system to train with a negative impedance, essentially a form of energetic assistance, and then successfully apply learned skills to a completely passive environment. Researchers have already shown [16]-[17] that stroke survivors can improve manual skills with a device that reduces the influence of gravity on the arm. Similar to negative impedances, such conditions facilitate intended movements yet preserve the inertial aspects of arm dynamics. Further study is needed to determine how training with negative impedance influence long term skill acquisition, as well as how such conditions compare with other forms of robotic training.

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REFERENCES

[1] Kazerooni, H., "The Human Power Amplifier Technology at the University of California, Berkeley," *Journal of Robotics and Autonomous Systems*, Elsevier, Volume 19, 1996, pp. 179-187.

[2] Gabriel Aguirre-Ollinger, J. Edward Colgate, Michael A. Peshkin, Ambarish Goswami: A 1-DOF assistive exoskeleton with virtual negative damping: effects on the kinematic response of the lower limbs. IROS 2007: 1938-1944

[3] JL Patton and FA Mussa-Ivaldi, "Robot-assisted adaptive training: custom force fields for teaching movement patterns," *Biomedical Engineering, IEEE Transactions on*, vol. 51, no.4, pp. 636–646, 2004.

[4] JL Patton, M Stoykov, M Kovic, and FA Mussa-Ivaldi, "Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors," *EBR*, vol.168, pp.368–383, 2006.

[5] J. R. Flanagan and S. Lolley, "The Inertial Anisotropy of the Arm Is Accurately Predicted during Movement Planning," *J. Neurosci.*, vol. 21, no. 4, pp. 1361–1369, 2001.

[6] Spong et al., 2005 M.W. Spong, S. Hutchinson and M. Vidyasagar, "Robot modeling and control", Wiley, New York (2005).

[7] Takahashi CD, Reinkensmeyer DJ. Hemiparetic stroke impairs anticipatory control of arm movement. Exp Brain Res. 2003 Mar;149(2):131-40. Epub 2003 Jan 30.

[8] Wei Y, Bajaj P, Scheidt R, Patton JL: Visual Error Augmentation for Enhancing Motor Learning and Rehabilitative Relearning. In IEEE Int. Conference on Rehabilitation Robotics. Chicago, IL; 2005.

[9] Y. Matsuoka, B. Brewer, and R. Klatzky, "Using visual feedback distortion to alter coordinated pinching patterns for robotic rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 4, no. 1, p. 17, 2007.

[10] H. Sveistrup, "Motor rehabilitation using virtual reality," *Journal of NeuroEngineering and Rehabilitation*, vol. 1, no. 1, p. 10, 2004.

[11] E. Todorov, R. Shadmehr, and E. Bizzi, "Augmented feedback presented in a virtual environment accelerates learning in a difficult motor task," *Journal of Motor Behaviour*, vol. 29, no. 2, pp. 147–158, November 1997.

[12] P. N. Sabes, M. I. Jordan, and D. M. Wolpert, "The Role of Inertial Sensitivity in Motor Planning," *J. Neurosci.*, vol. 18, no. 15, pp. 5948–5957, 1998.

[13] S. Schaal, D. Sternard, and C. G. Atkeson, "One-handed juggling: A dynamical approach to rhythmic movement task," *Journal of Motor Behavior*, vol. 2, no. 28, pp. 165–183, 1996.

[14] L. Kahn, M. Zygman, W. Z. Rymer, and D. Reinkensmeyer, "Robot-assisted reaching exercise promotes arm movement recovery in chronic hemiparetic stroke: a randomized controlled pilot study," *J. of Neuro Engineering and Rehabilitation*, vol. 3, no. 1, p. 12, 2006.

[15] M. J. Johnson, H. F. M. Van der Loos, C G. Burgar,P. Shor, L. J. Leifer, "Experimental results using force-feedback cueing in robot-assisted stroke therapy," *IEEE Trans Neural Systems & Rehab Engng*, vol. 13, pp. 335–348, 2005.

[16] S. Housman, V. Le, T. Rahman, R. Sanchez, and D. Reinkensmeyer, "Arm-training with t-wrex after chronic stroke: Preliminary results of a randomized controlled trial," *Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, Noordwijk, Netherlands*, pp. 562–568, June 12-15.

[17] R. Sanchez, J. Liu, S. Rao, P. Shah, R. Smith, T. Rahman, S. Cramer, J. Bobrow, and D. Reinkensmeyer, "Automating arm movement training following severe stroke: functional exercises with quantitative feedback in a gravity-reduced environment." *IEEE Trans Neural Syst Rehabil Eng.*, vol. 14, no. 3, pp. 368–389, 2006.