



Characterization of Neural Tuning: Visual Lead-in Movements Generalize in Speed and Distance

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Abstract. Prior work has shown that independent motor memories of opposing dynamics can be learned when the movements are preceded by unique lead-in movements, each associated with a different direction of dynamics. Here we examine generalization effects using visual lead-in movements. Specifically, we test how variations in lead-in kinematics, in terms of duration, speed and distance, effect the expression of the learned motor memory. We show that the motor system is more strongly affected by changes in the duration of the movement, whereas longer movement distances have no effect.

1 Introduction

Recent studies have highlighted some of the critical aspects for rehabilitation of neurological disorders or injuries using robotic systems [1]. Continuing progress depends on understanding the mechanisms of human sensorimotor learning in order to determine the optimal presentation of sensory information to improve the rate, retention and generalization of adaptation. Studies in healthy humans have shown that interference of simultaneous learning of opposing dynamics can occur, preventing learning in the absence of appropriate sensory cues [2]. Our recent work has shown that in such cases both prior movement [3, 4] and future movement [5] can be used to cue the learning of independent motor memories where the effect, at least for future movements, depends on the planning of the movement rather than the execution [6].

These phenomena, along with the requirement of close temporal association, whereby the lead-in or follow-through movement needs to occur within 500 ms of the adaptation movement [3], has suggested a strong link with the theory of neural population dynamics [7, 8]. In this framework movements are prepared in neural space and

Financial support was provided by the Wellcome Trust and the Centre for Robotics and Neural Systems at Plymouth University.

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L. Masia et al. (Eds.): ICNR 2018, BIOSYSROB 21, pp. 1030–1033, 2019.

https://doi.org/10.1007/978-3-030-01845-0_206

then unfold according to the temporal evolution of a dynamical system. These associated movements affect the learning rate, the generalization and the interference seen as participants learn novel dynamics. Previous work has demonstrated that the neural tuning functions of lead-in movements exhibit Gaussian-like angular tuning [9–11]. Here we further characterize this tuning as the distance, speed and duration of the visual lead-in movement are varied.

2 Materials and Methods

2.1 Experimental Design

Eight participants (6 female; aged 27.4 ± 6.7 years, mean \pm SD) performed the experiment over two days (~ 3 h per day). All participants were right handed, naïve to the aims of the study, and provided written informed consent before participation. The study was approved by the University of Cambridge Ethics Committee.

Experiments were performed using a vBOT planar robotic manipulandum [12]. Participants grasped the robot handle in their right hand while their right forearm was supported by an air sled, constraining arm movement to the horizontal plane. Participants could not view their hand directly. Instead veridical visual feedback was used to overlay images of the cursor, starting location, via point, and final target in the plane of movement. Details of the apparatus and experimental design can be found in our prior work [9, 10].

Each trial consisted of a two-part movement: a lead-in movement (a distinct movement of the hand or cursor) followed immediately by an adaptation movement. Here the lead-in was a minimum jerk visual motion of the cursor from the start to the via-point, while the participant's hand remained stationary at the via-point location. The adaptation movement was then actively performed by the participants from the via-point to the final target during which either a null field, a curl force field or a mechanical channel was applied. The lead-in movement was always oriented at either $+45^\circ$ or -45° to the adaptation movement, where the direction of each lead-in movement was uniquely associated with the direction of curl force field. For training trials the adaptation movement was performed in a null field (pre-exposure phase) or force field (exposure phase), and the lead-in movement was always 10 cm distance with 700 ms duration.

Generalization of the learning associated to the lead-in movement was tested with different lead-in kinematics using channel trials. On these trials, the lead-in movement was chosen from one of 15 different movements with distances ranging from 3 cm to 20 cm and durations ranging between 210 ms to 1400 ms. On all these movements the adaptation movement was always performed within a mechanical channel [13] such that any predictive learned compensation could be measured from the force exerted into the channel.

Experiments started with the pre-exposure phase (262 trials) in which participants made movements in the null field. During the exposure phase (2816 trials over two days), the two opposing curl force fields were introduced on the adaptation movement. During both the pre-exposure and exposure phases, generalization movements were performed on random trials to obtain a baseline measurement and test the extent of generalization after adaptation.

2.2 Analysis

Experimental data was analyzed offline using Matlab. Kinematic error (maximum perpendicular distance) was calculated on the null and force field trials. The level of force compensation [14] was assessed on channel trials for different lead-in motions to examine the generalization functions.

3 Results

When presented with the curl force field, participants' adaptation movements were disturbed, producing large errors that were gradually reduced over the exposure phase. Over a similar timescale, force compensation increased, reaching approximately 90% compensation for both force fields.

In the generalization movements, the force compensation decreased as the lead-in movement deviated further away from the trained movement for duration, distance, or peak speed (Fig. 1). However, this fall-off was smallest when duration was matched (red), with almost no decrement up to 20 cm lead-in distance. In contrast, when peak speed was matched (green) the generalization falloff was greatest as duration (and therefore distance) were varied.

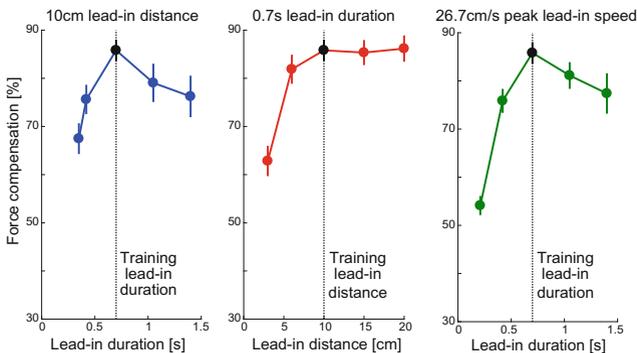


Fig. 1. Generalization of the predictive force compensation (mean \pm se) as the lead-in movement duration, speed and/or distance are varied away from the trained lead-in movement values (dotted line). The plot title shows the kinematic measure that was matched to the training movement while variations in the other measures occurred. Note that measures are not independent such that both duration and speed vary if distance is fixed.

4 Discussion

In this study we examined the generalization of learning with variations in the visual lead-in kinematics. We found that as movement duration or peak speed deviate from the training movement, the expressed force compensation decreases. However, while shorter distances exhibit a similar fall off, increases in distance produced no change in

the force. These results further characterize the neural tuning of the lead-in movements, extending beyond the directional tuning seen previously [9–11]. We suggest that these affects may arise through state estimation, whereby multiple sensory signals are combined with efference copy to estimate the future location of the limb. It has been shown that variability in the lead-in movements can affect the speed of adaptation depending on the size of this generalization function [4]. Our current results suggest that variations in the speed or duration of these lead-in movements could provide similar decrements in learning rate, and such variations should therefore also be minimized to maximize learning speed of novel dynamics.

References

1. Reinkensmeyer, D.J., Burdet, E., Casadio, M., Krakauer, J.W., Kwakkel, G., Lang, C.E., Swinnen, S.P., Ward, N.S., Schweighofer, N.: Computational neurorehabilitation: modeling plasticity and learning to predict recovery. *J. Neuroeng. Rehabil.* **13**(1), 1–26 (2016)
2. Howard, I.S., Wolpert, D.M., Franklin, D.W.: The effect of contextual cues on the encoding of motor memories. *J. Neurophysiol.* **109**(10), 2632–2644 (2013)
3. Howard, I.S., Ingram, J.N., Franklin, D.W., Wolpert, D.M.: Gone in 0.6 seconds: the encoding of motor memories depends on recent sensorimotor states. *J. Neurosci.* **32**(37), 12756–12768 (2012)
4. Howard, I.S., Ford, C., Cangelosi, A., Franklin, D.W.: Active lead-in variability affects motor memory formation and slows motor learning. *Sci. Rep.* **7**(1), 7806 (2017)
5. Howard, I.S., Wolpert, D.M., Franklin, D.W.: The value of the follow-through derives from motor learning depending on future actions. *Curr. Biol.* **25**(3), 397–401 (2015)
6. Sheahan, H.R., Franklin, D.W., Wolpert, D.M.: Motor planning, not execution, separates motor memories. *Neuron* **92**(4), 773–779 (2016)
7. Churchland, M.M., Cunningham, J.P., Kaufman, M.T., Foster, J.D., Nuyujukian, P., Ryu, S. I., Shenoy, K.V.: Neural population dynamics during reaching. *Nature* **487**(7405), 51–56 (2012)
8. Pandarinath, C., Gilja, V., Blabe, C.H., Nuyujukian, P., Sarma, A.A., Soric, B.L., Eskandar, E.N., Hochberg, L.R., Henderson, J.M., Shenoy, K.V.: Neural population dynamics in human motor cortex during movements in people with ALS. *Elife* **4**, e07436 (2015)
9. Howard, I.S., Franklin, D.W.: Adaptive tuning functions arise from visual observation of past movement. *Sci. Rep.* **6**, 28416 (2016)
10. Howard, I.S., Franklin, D.W.: Neural tuning functions underlie both generalization and interference. *PLoS ONE* **10**(6), e0131268 (2015)
11. Sarwary, A.M.E., Stegeman, D.F., Selen, L.P.J., Medendorp, W.P.: Generalization and transfer of contextual cues in motor learning. *J. Neurophysiol.* **114**, 1565–1576 (2015)
12. Howard, I.S., Ingram, J.N., Wolpert, D.M.: A modular planar robotic manipulandum with end-point torque control. *J. Neurosci. Methods* **181**(2), 199–211 (2009)
13. Scheidt, R.A., Reinkensmeyer, D.J., Conditt, M.A., Rymer, W.Z., Mussa-Ivaldi, F.A.: Persistence of motor adaptation during constrained, multi-joint, arm movements. *J. Neurophysiol.* **84**(2), 853–862 (2000)
14. Smith, M.A., Ghazizadeh, A., Shadmehr, R.: Interacting adaptive processes with different timescales underlie short-term motor learning. *PLoS Biol.* **4**(6), e179 (2006)