Generalization patterns reveal that visuomotor adaptation is composed of two distinct components

Jordan B. Brayanov, Biljana Petreska and Maurice A. Smith - Harvard University School of Engineering

Visuomotor rotation learning (VMRL) and visuomotor gain learning (VMGL) have been extensively studied as models of how visuomotor transformations might be processed by the motor system. Previous work has suggested that when VMRL is trained in a single target direction, generalization is limited to nearby movement directions, while VMGL trained under analogous conditions generalizes to all directions (Pine et al 1996, Krakauer et al 2000). More specifically, the generalization of VMRL falls off over a range of 45°, while VMGL displays a high level of adaptation 180° away from training.

Here we train both VMRL and VMGL in a single movement direction in a large number of subjects (n=42 in total) and densely sample the patterns of generalization across other movement directions (every 15°) as shown in Fig 1. We first performed a one-dimensional analysis of the generalization data (like that presented in Krakauer et al 2000 and other studies) by analyzing the circumferential components of the adaptation vectors for VMRL and the radial components of these vectors for VMGL. Our results show that these 1-D generalization functions appear to be comprised of a local Gaussian-shaped component as well as a global offset component for both VMRL (Fig 2A) and VMGL (Fig 2C). In the rotation learning data the local component accounts for 70% of the learning at the trained movement direction and has a width (σ) of 32°±2°. In the gain learning data the local component accounts for only 40% of the learning at the trained movement direction but has a remarkably similar width (σ=35°±3°). For both learning paradigms, we find that a model with a local and a global component explains the generalization data remarkably well (R²=97% for VMR and R²=93% for VMGL), yielding substantially lower residual errors than global-only or local-only models as shown in Fig 2B & 2D (p<0.0001 in all cases).

We further investigated the behavior of the two learning components by analyzing the two-dimensional patterns of end-point errors in the generalization data. In examining the VMRL data (Fig 3A), we noticed that the adaptation vectors were not perfectly circumferential as would be predicted by an intrinsically-rotational generalization pattern. This suggested that either the local component of generalization might be a local shift (LS) rather than a local rotation (LR) or that the global component might be a global shift (GS) rather than a global rotation (GR). We found that a GR+LS model explained a remarkable 98.7% of the variance in the 2-D adaptation vectors as shown in Fig 3D. Qualitative evidence for this model is presented in panels B & C of Fig 3: When a global rotation is subtracted from the adaptation vectors, the residual vectors (blue arrows in Fig 3B) tend to all point in the same direction, as would be predicted if a local shift occurred in conjunction with a global rotation. Correspondingly, when a local shift is subtracted from the adaptation vectors, the residual vectors (yellow arrow in Fig 3C) tend to be aligned circumferentially. Quantitatively, the GR+LS model accounts for the 2-D generalization data better than 3 other local-global models (GS+LR, GS+LS, GR+LR) with at least 3 times smaller residual errors (Fig 3E, p<0.001 in all cases). Based on this finding, we conclude that the local component of rotation learning provides a contribution to the adaptation vector whose amplitude depends strongly on the movement direction but whose orientation does not. In contrast, the global component displays a complementary set of properties. It provides a contribution to the adaptation vector that has an amplitude that is independent of movement direction but an orientation that strongly depends on it. Thus the global component’s orientation is movement direction dependent, but the local component’s orientation is not.

When we repeated the 2-D adaptation vector analyses on the generalization data from the VMGL experiment, we found that not only are both the local and global components present, but the global component is direction-specific, just as with the VMRL experiment (Fig 3F). However, we could not conclusively determine whether the local component is direction dependent or direction independent, as both explain the data equally well (p>0.5). Note that here direction-independent generalization corresponds to a shift as in the VMRL experiment, while direction-dependent generalization corresponds to a gain rather than a rotation. Our findings demonstrate that distinct local and global components underlie the learning of multiple types of visuomotor transformations. However rotation learning displays a larger local component whereas gain learning displays a larger global component, in line with previous data. Further work will be needed to understand the mechanisms for determining the sizes of the local and global components that we have uncovered.
Figure 1: Experimental paradigm. In experiment 1, 20 subjects adapted to a 30° visuomotor rotation (10 to a 30° CW and 10 to a 30° CCW rotation) while reaching to a single target location (purple box). After a training period of 120 trials with real-time visual feedback, we measured the directional generalization function in 19 movement directions as shown on the right. Generalization was measured without visual feedback. In experiment 2, 22 additional subjects adapted to a visuomotor gain of either 1.75 or 0.7 while reaching to a single target location (brown box). Both gains correspond to the same movement length change, a decrease or increase of 39 mm (43%).

Figure 2: One-dimensional generalization functions. (A) Generalization function (GF) for visuomotor rotation learning. Note that this GF is well described by the sum of two components: a Gaussian local (blue shaded region), and uniform global (yellow region) component. At the trained direction the local component accounts for 70% of the learning, however, this contribution drops to only 40% when integrated over the whole workspace (inset). (B) Residual errors after fitting global-only (G), local-only (L), or combined (G+L) models to the data displayed on a log-scale. (C) and (D) same as (A) and (B) for visuomotor gain learning.

Figure 3: Two-dimensional generalization functions. (A) Adaptation vectors for visuomotor rotation learning. Black arrows represent the amount of adaptation to each target. Each vector originates at the average pre-training reach location and ends at the post-training reach location. (B) Residual vectors (blue arrows) after subtracting a global rotation. The global rotation itself has an R²=75% and the residual errors resemble a local shift (the blue residual vectors tend to all point in the same direction). (C) Residual vectors (yellow arrows) after fitting a local shift. The local shift itself has an R²=60% and the residual errors resemble a global rotation. (D) Combined model (green arrows) after fitting a global rotation plus a local shift (GR+LS) accounts for almost all of the data R²=98.7%. (E) Comparison of the four possible models for rotation learning that are combinations of global rotation (GR) or global shift (GS) learning with local rotation (LR) or local shift (LS) learning. The GR+LS model fits the data significantly better than the other three (** p<0.001 in all cases). (F) Comparison of the four possible models the gain learning that are combinations of global gain (GG) or global shift (GS) learning with local gain (LG) or local shift (LS) learning. Both models which include a global gain component fit the data equally well (p>0.5, R²>99% for both) and are significantly better than the models including a global shift (p<0.001 in all cases). Note that the residual errors in (E) and (F) are shown on a log-scale.