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Motor Learning in Suppressed Tracking Tasks

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We measured tracking performance in two groups while either the target or the manual cursor was suppressed for a brief period during each trial. We used this manipulation to show that motor learning involves acquiring predictive models of the target motion and also of one's own hand movement. We also found clear positive transfer from learning to predict one's own manual action to learning target motions, and no transfer in the reverse direction. This asymmetric transfer suggests specific predictive neural mechanisms for learning to control one's own action, as opposed to general prediction of external events.

Introduction

Tracking

Pursuit tracking is well-established experimental paradigm for studying motor learning (Poulton, 1974). The basic component of the tracking response is assumed to involve visual feedback-error-driven correction. Several lines of evidence suggest, however, that tracking is not purely feedback-driven, but also involves prediction. Subjects can track accurately even when absence of either the target or the cursor signal makes error-detection impossible (Beppu et al., 1987).

Internal models

The predictive element of tracking is often attributed to learning of internal models. Tracking performance could potentially involve two separate internal forward models. One model would estimate or predict the current position of the target based on its previous kinematic history. Another would estimate or predict the current position of the hand-cursor, based on the current motor command and any available proprioceptive feedback. We will call these putative models the **target model** and **motor model** respectively.

Learning is a key feature of all internal models. According to one computational theory, visual feedback error provides an important learning signal which can be used to update the internal models (Kawato & Gomi, 1992).

Suppressed task

One promising method for investigating the possible dissociation of target and motor models in tracking involves comparing the effects of target suppression and cursor suppression (Beppu et al., 1987). In target suppression, subjects track a predictably moving target. The target disappears at some point during the track, while the cursor remains visible. In cursor suppression, the cursor disappears but the target remains visible. Subjects continue to track for some interval, and the target or cursor display is then restored. No visual error signal is present during target-suppressed and cursor-suppressed tracking. Target and cursor are not simultaneously visible, so their discrepancy cannot be computed.

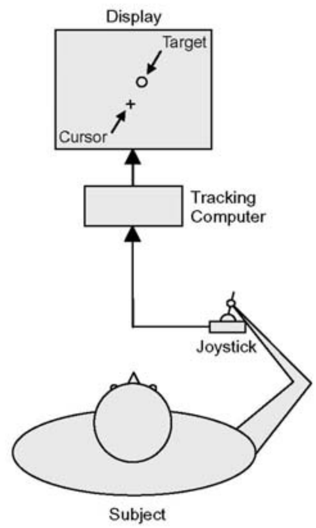

Figure 1: Experimental apparatus.

The aim of this study

We have used the target and cursor suppression approach to investigate the internal models used during tracking, and their updating during motor learning. We have focused on identifying differences in tracking behavior between target and cursor suppression conditions. If target-suppressed and cursor-suppressed conditions show differences in either short-term performance, or in longer-term learning, then this would provide strong evidence for the existence of separate and dissociable internal models for these two components of skilled action. We therefore measured tracking error during both target and cursor suppression, and described the learning curve in each condition.

We assumed that suppression tracking involves a number of dissociable processes. First, when the target or cursor disappears and suppressed tracking begins, the subject must rely on internal model-based tracking. Second, when the target or cursor reappears, a second, visual feedback process will detect any error, and issue a feedback-driven motor correction. We wanted to distinguish between these two processes.

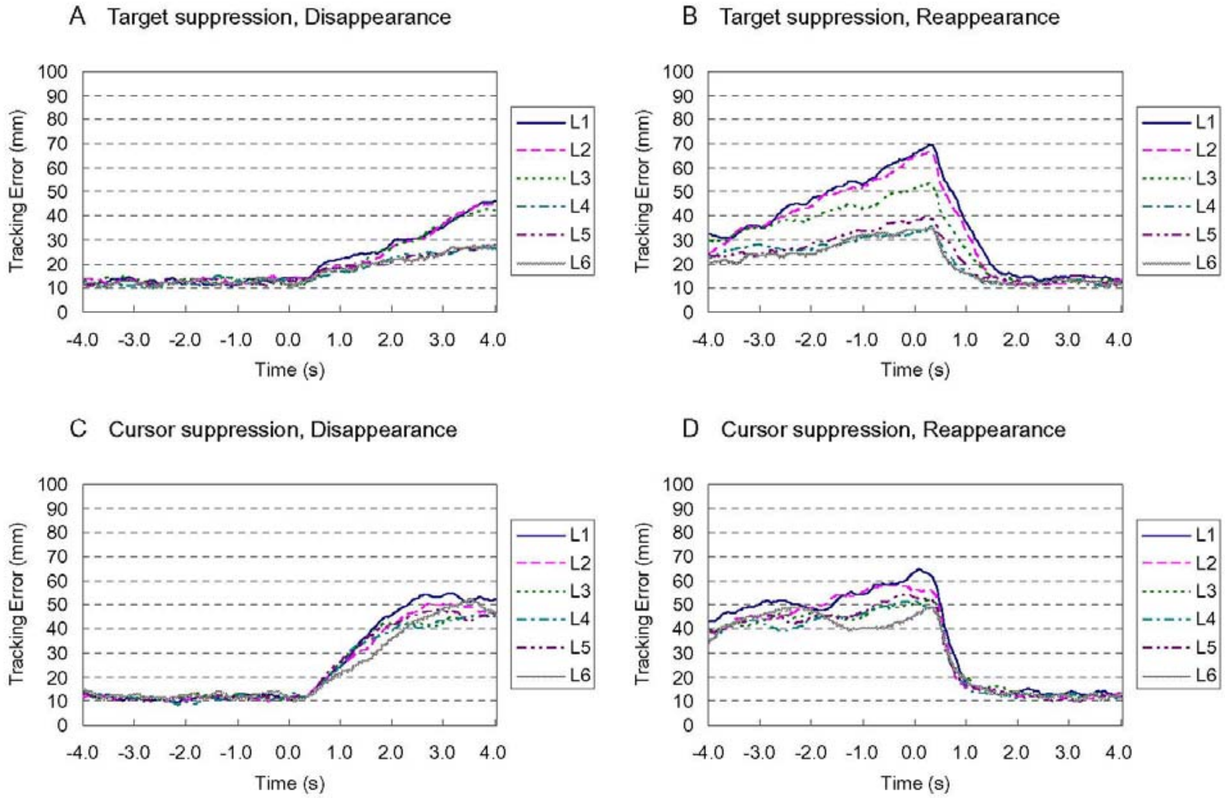

Figure 2: Grand average tracking error waveforms arranged by learning block.

Finally, we investigated whether tracking involves learning just one internal model, or involves separate target and motor models using a learning transfer approach.

Methods

Apparatus

The apparatus is shown in Figure 1.

Tracking

Subjects observed a circular target moving at constant tangential velocity along a clockwise circular trajectory on a computer screen. The target cycle was 5 sec. The viewing distance was 66 cm. Each trial lasted 20 sec. Subjects held a modified joystick in their right hand, and moved it so that a visual cross hair cursor tracked the target as closely as possible.

Tracking trials were of 2 types, normal and suppressed tracking. In normal trials, the movements of the joystick produced congruent movements of the subject's cursor on the screen. In suppressed tracking, we blanked out either the target or the cursor during the trial. The disappearance occurred at an unpredictable time between 5 and 7 sec. Then, the target or cursor reappeared at a random time between 11 and 13 sec.

Experimental design

All experimental blocks consisted of 5 trials. The experiment began with a pretest block of normal tracking trials.

Next, subjects performed 6 learning blocks of target or cursor suppressed trials each. Then, subjects performed a posttest block of normal trials similar to the pretest block The experiment ended with 2 transfer blocks of the other kind of suppressed trials which was not performed in the learning phase.

The subjects were instructed to continue tracking as accurately as possible when target or cursor disappeared.

20 subjects were recruited from among the students of Ryukoku University. Subjects' ages ranged between 19 and 24 years. 10 subjects were male, and 10 were female.

We divided the subjects into 2 groups. The target suppression group performed target-suppressed trials in the learning blocks and cursor-suppressed trials in transfer blocks. The cursor suppression group performed cursor-suppressed trials in learning blocks and target-suppressed trials in transfer blocks.

Results

Tracking data

The grand average traces of unsigned tracking error for each learning block are shown in Figure 2. Data from suppressed trials are aligned either to the time of disappearance, or the time of reappearance as appropriate.

Figure 2 shows that the error during the suppression period varies across the learning blocks. In the target suppression group, tracking error is clearly higher for blocks 1-3 than blocks 4-6. The cursor suppression group also shows differences between blocks, but these are somewhat smaller than in the target suppression group.

We calculated mean tracking error on each trial during an epoch from the time of disappearance to 2 sec after reappearance. We compared the tracking error in the first and last learning blocks, using a mixed ANOVA with factors of group (between-subjects) and block (within-subjects). This showed a significant effect of block [$F(1,18) = 11.514$, $p = .003$] with lower tracking error in block 6 than in block 1, as predicted. There was no significant effect of group [$F(1,18) = 3.701$, $p = .070$] and no interaction [$F(1,18) = 1.859$, $p = .190$]. We also compared the tracking error in the first and last learning blocks in each group separately. The results showed significant effects of learning in target suppression group [$t(18) = 2.722$, $p = .0007$] and also in cursor suppression group [$t(18) = 1.923$, $p = .0035$]. Thus, subjects learned to track during the suppression period.

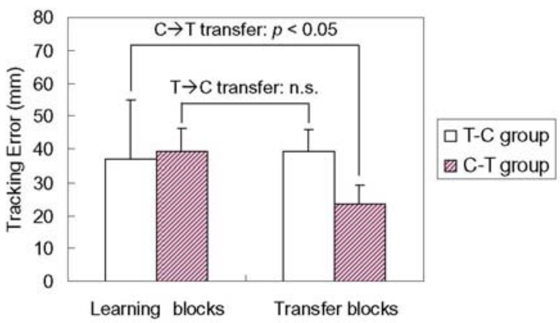

Figure 3: Transfer of learning.

Transfer of Learning

We investigated transfer of internal-model learning by comparing tracking performance on the two transfer blocks with tracking performance on the first two learning blocks (Adams, 1987).

We subjected the tracking error data to a mixed ANOVA model with factors of learning group (target suppression, cursor suppression) and learning phase (learning, transfer). The results showed a non-significant effect of group [$F(1,18) = 4.188$, $p = .056$], with those initially learning cursor suppression showing slightly better performance overall. There was a significant effect of learning phase [$F(1,18) = .401$, $p = .021$], due to an overall positive transfer effect. That is, performance in the transfer blocks was significantly better than initial learning. Most importantly, there was a significant interaction [$F(1,18) = 11.341$, $p = .003$]. Follow-up simple effects testing was used to investigate the source of this interaction. The results are shown in Figure 3. The group who initially learned with target suppression, showed a non-significant negative transfer to subsequent testing with cursor suppression [$t(18) = .001$, n.s.]. In contrast, the group who initially learned with cursor suppression showed significant positive transfer to subsequent testing with target suppression [$t(18) = 2.460$, $p = .024$].

Conclusions

We measure tracking performance in two separate groups of participants while either the target or the manual cursor was suppressed for a brief period during each tracking trial. Subjects learned to maintain accurate tracking through periods of target or cursor suppression. During the suppressed period, feedback-error-driven mechanisms cannot be used, and tracking performance therefore relies on prediction alone. We used this manipulation to show that motor learning involves acquiring predictive models of the target motion and also of one's own hand movement. We also used a transfer of learning design to investigate whether acquiring models of target motion and of one's own hand motion involved linked or independent neural modules. We found clear positive transfer from learning to predict one's own manual action to learning target motions, and no evidence for transfer in the reverse direction. This asymmetric pattern suggests specific predictive neural mechanisms for learning to control one's own action, as opposed to general prediction of external events. We suggest that learning internal representations of one's own motor systems may play an important role in learning about the perceptual world.

Acknowledgments

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