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# Performance feedback engages attention, boosts task SNR, and enhances pattern classification


Jeffrey C. Zemla[1], Jonathan M. Lisinski[1], and Stephen LaConte[1,2]

[1]Virginia Tech Carilion Research Institute, Roanoke, VA

[2]School of Biomedical Engineering and Sciences, Virginia Tech, Blacksburg, VA


## Introduction

An essential part of learning involves the perception and evaluation of feedback to actively modify one's behavior. A critical question, however, is whether or not neural signatures from fMRI can be used to evaluate and even optimize behavioral and/or neurofeedback interfaces. This study explores the role of feedback on attention networks in the brain. Specifically, we asked subjects to perform a visually-paced finger tapping task with and without behavioral performance feedback. Our findings suggest that feedback increases BOLD signal in right fronto-parietal attention networks, increases prediction accuracy of pattern classifiers, and increases whole brain signal-to-noise ratio (SNR).

## Methods

- 13 subjects recruited for a visually paced finger tapping fMRI study (3 T, TR/TE=2000/30ms)
- Participants watch a cross flash on the screen at either fast or slow rates while mentally keeping pace
- Participants tap using their right index finger at the pace they had just watched
- 72 trials, evenly divided among three conditions: a) no feedback, b) noisy feedback, and c) good feedback (Fig. 1)

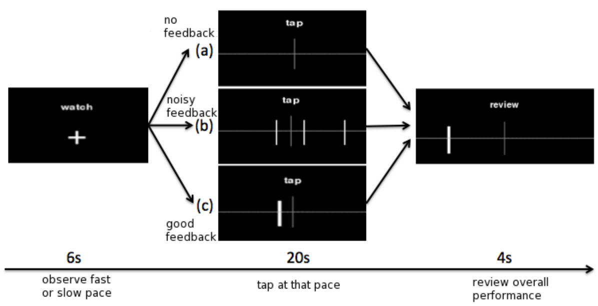


Figure 1: (a) In the no feedback condition, subjects were not told if they were tapping too fast or too slow. (b) In the noisy feedback condition, a group of three bars gave subjects a rough approximation of their tapping rate. (c) In the good feedback condition, a solid bar indicated the subject's exact tapping rate.

## Behavioral Results

- Two-way repeated-measures ANOVA (feedback condition and tapping rate)
- Main effect of tapping rate on performance (p=.002)
  - ▷ Better performance during slow tapping compared to fast tapping
- Main effect of feedback condition on performance (p=.014)
  - ▷ Post-hoc t-tests show good feedback yields better performance than no feedback (p=.015)
  - ▷ Noisy feedback yields better performance than no feedback (p=.036)
  - ▷ No difference between two feedback conditions (p=.95)

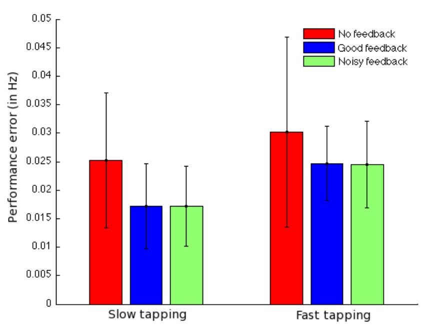


Figure 2: Subjects performed better at slow compared to fast tapping rates, and also performed better in feedback compared to non-feedback conditions.

## Fronto-parietal Network

- Fronto-parietal network has been implicated in functions such as attention and tool use (Corbetta et al., 2008; Culham et al., 2008)
- We saw an increased signal in fronto-parietal networks (e.g., BA40 and BA6) for a feedback > no feedback contrast in a whole-brain GLM
- This network may be partially responsible for an increase in attention and thus improved performance as a result of behavioral feedback

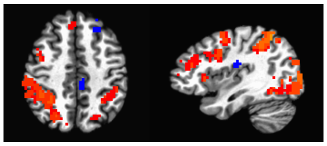

Figure 3: The right fronto-parietal network, including BA6 and BA40, are more active during feedback compared to non-feedback conditions. Significant activation was also found in the R inferior frontal gyrus/BA9, R inferior parietal lobule, and R middle frontal gyrus. Activations are thresholded at p=.05, FDR corrected.

## Fronto-parietal Network (cont.)

- Rise in signal in BA6/BA40 during the tapping phase for feedback but not for non-feedback conditions
- Paired t-tests show a significant difference between good feedback and no feedback for TRs 5-9, Bonferroni corrected
- Noisy feedback (not shown) shows a pattern that largely overlaps with good feedback

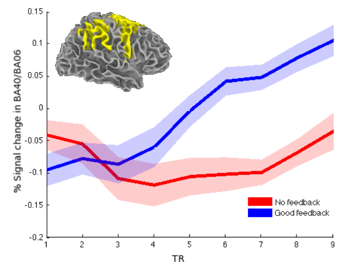


Figure 4: In the good feedback condition (blue), the signal in BA6/BA40 steadily rose during the tapping period. In contrast, during the no feedback condition (red) the signal in these areas stayed relatively stable for the duration of tapping. Each data point indicates a time-locked block average across all participants.

## Pattern Classification

- Does feedback lead to improved pattern classification?
- AFNI's 3dsvm command (Cox, 1996; LaConte et al., 2005) was used to create linear support vector machine (SVM) classifiers to distinguish fast vs slow tapping
  - ▷ SVMs were trained on each feedback condition and tested against the remaining two conditions
- No difference in prediction accuracy (PA) by condition for whole-brain SVMs
- PA was higher when testing on feedback conditions (71%) compared to non-feedback conditions (68%) when the SVM was limited to motor regions (BA1-5)
- This difference was not significant (p=.12), but provides some support for previous findings (LaConte et al., 2007; Papageorgiou et al., 2009)

## Signal to Noise Ratio (SNR)

- We hypothesized that utilizing feedback requires increased attention, which may modulate whole-brain signal-to-noise ratio (SNR) and lead to better classifier accuracy
- We examined SNR by looking at the reproducibility of the SVM weight vector maps between feedback and non-feedback conditions using the NPAIRS framework (Strother et al., 2002; Fig 5)
- We compared SVM maps for good feedback vs no feedback by sweeping through map thresholds, analogous to what is done in an ROC analysis
  - ▷ Feedback SVM models are more sensitive to a small subset of voxels with high weights
  - ▷ No feedback SVM models results in voxels weights which are more uniform, suggesting a lower SNR

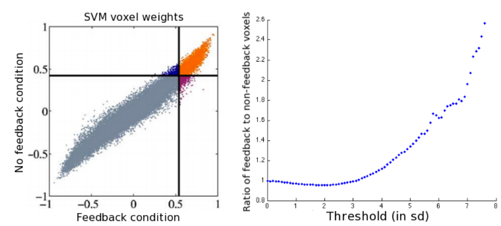


Figure 5: The left graph shows a scatterplot of voxel weights for two runs of the same task. Tasks whose SVM weight maps are highly reproducible will show an ellipse along the signal axis, whereas tasks with poor reproducibility will appear more spherical. The right graph shows ratios of the number of feedback to non-feedback voxels at different thresholds for the current dataset. (Left figure from LaConte et al., 2005.)

## Conclusions

- Behavioral feedback increased BOLD signal in right fronto-parietal regions
- Feedback improved behavioral performance
- This network could be responsible for modulating task-based tapping activity, leading to increased task SNR in the presence of feedback
- Increases in prediction accuracy and SNR may have implications for pattern-based real-time fMRI (LaConte, 2007), and more generally to any fMRI study where performance feedback is presented to subjects

## References


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