Predictive Eye Estimation Regression (PEER) for Simultaneous Eye Tracking and fMRI

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INTRODUCTION Eye tracking is a common behavioral measure for cognitive studies and is often a valuable complement to fMRI, particularly for experiments that require visual fixation. The most common approach in an fMRI environment is to use reflected infrared light from the cornea to track eye movement and determine fixation. Installation of such a system can pose a significant challenge since the optics and path of the transmitted and reflected infrared light usually must avoid interference with the visual paradigm display. During an experiment, setup of the optics extends time in a manner that can vary from subject to subject. Another obvious drawback is that fMRI compatible eye-tracking systems are generally expensive. Here we propose PEER (Predictive Eye Estimation Regression) - a simple alternative that is adequate for determining fixation on a TR-by-TR basis. In this approach, calibration, instead of being performed right before scanning, takes place during an added imaging run whose sequence parameters match those of the fMRI scans (slice prescription, TR, TE, flip angle, bandwidth, etc). Support vector regression (SVR) [1] is then used to model each calibration image and its corresponding (known) fixation location. This model can then be used to predict eye fixation during the session's fMRI runs.

METHODS Imaging: fMRI data were collected on a 3T Siemens Trio, with 27 axial EPI slices (TR/TE = 2000/31 msec, voxel=3.4 × 3.4 × 5 mm). The stimulus display software used was Presentation® (www.neurobs.com). We used back projection to a mirror mounted within the head coil and provided an approximate visual field of 20˚ horizontally and 15˚ vertically. For three volunteers, we performed three imaging runs, each lasting approximately 3 min. During the calibration run, the volunteer focused their gaze on a fixation symbol that moved to a random location on the display at each TR. The second run consisted of the volunteer fixating on the symbol placed at the center of the visual field for approximately 1 min., followed by two 30 s fixation periods with the symbol off center (above and to the right of center and below and to the left of center) and then returning to center fixation for the final minute. The third run matched the first calibration run (with a new randomization). Analysis: We modeled the first run using multivariate SVR [1]. In our current approach, a separate regression model was used for horizontal and vertical fixations. These calibration models were used to estimate the horizontal and vertical locations for the latter two runs.

RESULTS The figure below shows tracking results for a single subject: A) represents the fixation run, while B) shows the random position changes at each TR for run 3. The horizontal tracking (not shown) tended to be comparable or slightly worse than the vertical results in terms of goodness of fit (horizontal correlations ranged from 0.65 to 0.85 for the three subjects compared to vertical correlations of 0.78 to 0.92).

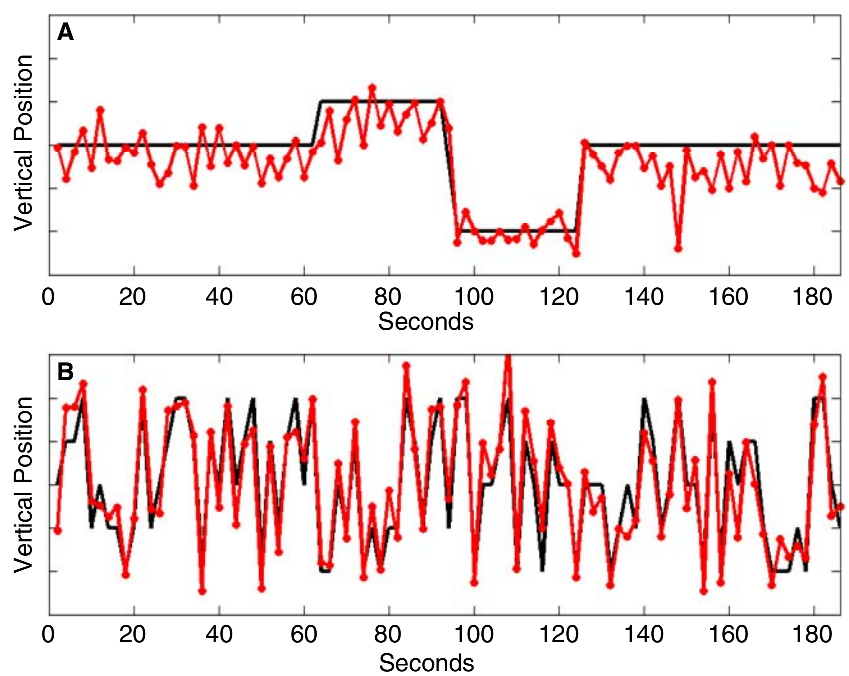

Figure 1. Vertical Tracking for a Single Subject. Red lines represent estimated tracking. Black represents symbol position. A) represents the fixation run, while B) shows the random position changes at each TR for run 3.

DISCUSSION AND CONCLUSION The idea of eye tracking with MRI is, to our knowledge, completely novel. It is important to note that PEER does not alter fMRI results, and, as a retrospective analysis tool, it can be applied at any fMRI site. As such, it is possible to acquire the calibration run at any point in the scanning session. Of course, extensions to real-time applications are also possible. Very rapid eye movements, such as saccades, would require much faster sampling frequencies. However, a great number of eye tracking applications only require information concerning fixation. Our preliminary results are encouraging and we anticipate that further refinements will advance the limits of temporal resolution and estimation precision.

REFERENCE [1] Vapnik, V. The Nature of Statistical Learning Theory, 1995.

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