Enhancing functional magnetic resonance imaging with supervised learning

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Abstract

This paper reports novel applications of supervised learning methods intended to directly impact fMRI technology with the aim of improving data acquisition and analysis.

1 Introduction

Within both the machine learning and cognitive neuroscience communities, there has been a remarkable surge in interest focused on brain state classification using functional magnetic resonance imaging (fMRI) data. This interest has been fostered by a growing number of fundamental methodological studies of brain state classification approaches [1-10] combined with an increasing awareness that such analyses can make profound contributions to how we interpret mental representations [11-17]. This has given rise to inventive experimental designs aimed at a broad number of applications ranging from unconsciously perceived sensory stimuli [18], behavioral choices in the context of emotional perception [19], early visual areas [20], information-based mapping [21], and memory recall [22].

This talk focuses on the author's work in applying supervised learning methods to directly impact fMRI technology with the aim of improving data acquisition and analysis. Specifically, we will describe i) the development of data-driven validation techniques for evaluating and optimizing the experimental parameters of image acquisition and analysis [3,4,8,10,8] ii) the recent implementation of a real-time fMRI biofeedback system based on brain state classification [23], and iii) the application of multivariate regression to achieve image-based eye tracking [24]. In addition, we will give a brief update on the status and capabilities of an AFNI [25] plugin that we have developed to enable support vector machine learning of fMRI data.

2 Data-driven validation

Neuroimaging techniques such as fMRI and positron emission tomography (PET) are unique among imaging modalities in terms of validation. Unlike a system for detecting fractures or tumors, there is no direct, independent method for verifying detected locations of brain activity. As an alternative to simulation-based receiver operator characteristic (ROC) analysis, our approach [3,4] applied the data analysis framework developed in [10] to generate prediction vs. reproducibility curves for evaluating methodological decisions of fMRI preprocessing. The curves shown in Fig. 1 represent motion correction, temporal filtering, spatial filtering, as well as model complexity. Favorable preprocessing methods are as far to the upper right hand corner of the plot as possible.

3 Real-time brain state feedback

Using brain state-based real time feedback (Fig. 2) is distinctly different from spatially localized real-time implementations since it does not require prior assumptions about functional localization and individual performance strategies. Since feedback is provided based on estimated brain state, the approach is applicable over a broad spectrum of cognitive domains and provides the capability for a new class of experimental designs in which real-time control of the stimulus is possible. This means that, rather than using a fixed paradigm, experiments can adaptively evolve as subjects receive brain-state feedback. In addition to describing our implementation and characterization of its basic performance capabilities, we will discuss the implications of human adaptation arising from feedback-enhanced learning and rehabilitation. Beyond basic research, this technology can complement electro-encephalography-based brain computer interface (EEG-BCI) research, and has potential applications in the areas of biofeedback rehabilitation, lie-detection, learning studies, virtual reality-based training, and enhanced conscious awareness.

4 Eye tracking

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 can become time consuming. Another obvious drawback is that fMRI compatible eye-tracking systems are generally expensive. We have recently proposed PEER (Predictive Eye Estimation Regression) as a simple alternative approach that is adequate for determining fixation on a TR-by-TR basis. With PEER, calibration, instead of being performed right before scanning, takes place during an added imaging run. Support vector regression (SVR) [26] is 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. The idea of eye tracking with MRI is 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 (Fig. 3) are encouraging and we anticipate that further refinements will advance the limits of temporal resolution and estimation precision.

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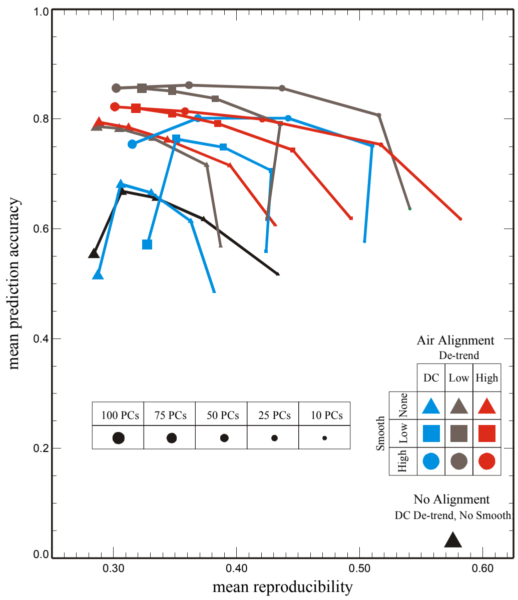

Figure 1. Prediction vs. reproducibility curves for data-driven evaluation of preprocessing choices in fMRI.

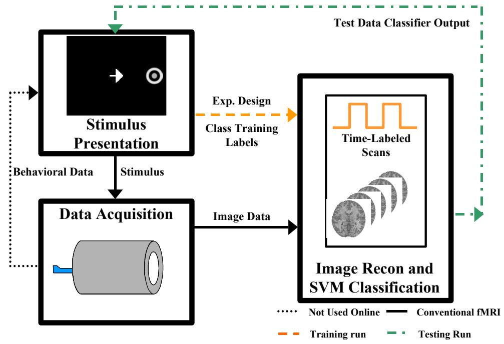

Figure 2. Block diagram of real-time classification of fMRI time-volumes using SVC.

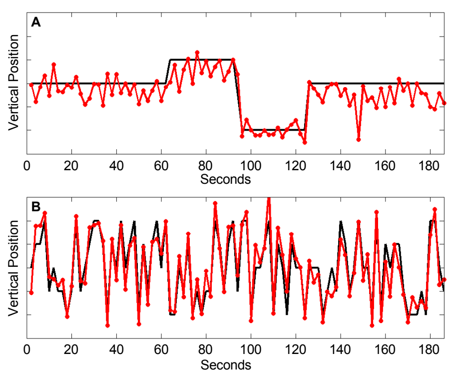

Figure 3. Vertical Tracking for a Single Subject. Red lines represent estimated tracking. Black represents symbol position. A) represents the fixation run, while B) shows the random position changes at each TR for run 3.