Title

# Abstract

Abstract text

# Introduction

Decoding cognitive states (refs) from fMRI opens up exciting new applications in training and therapy. However, many hurdles to clear before a real-world application is possible.

Training or therapy programs must be performed within the scanner. Virtual reality allows for broader range of possible programs. Some therapies already utilize virtual reality. See for example PTSD extinction therapy (refs). Cognitive state decoding must be accurate and reliable without imposing too many restrictions on the stimulus.

Most cognitive neuroscience experiments are focused on explanatory power at the expense of classification accuracy and stimuli complexity (makes sense when trying to answer a research question). However, our goal is to maximize decoding accuracy in a complex environment that could be used for training or therapy. Therefore, we propose the use of more complex multi-variate decoding techniques. They are more difficult to interpret but provide improved decoding accuracy.

Unfortunately, fMRI data is relatively ill posed for advanced machine learning methods. The dimensionality of whole brain data is large compared to the number of samples we can collect. Furthermore, the samples are correlated in both space and time. Many data-agnostic approaches have been used to solve this problem such as PCA and ICA. However, we want to use the structure of fMRI data and more specifically the brain to intelligently reduce the dimensionality of the data as much as possible before using something like PCA or ICA. We project the functional data on to extracted cortical surfaces by averaging through the gray matter normal to the surface. Only looking at signal from gray matter reduces the dimensionality of the data by a factor of #. Then we spatially smooth only along the surface thereby avoiding averaging our data with unwanted noise in the white matter and CSF. Furthermore, this also prevents averaging across sulcal/gyral boundaries where we no longer expect the signal to be spatially correlated. Finally, we down-sample on the surface based on our smoothing parameter to reduce the dimensionality again.

Most studies report within-session decoding accuracy. That is, the decoding accuracy on a held out test set from the same scanning session that the training data was collected in. It’s important to be able to train the classifier in one session, and then use that trained classifier in subsequent sessions (and potentially train a classifier on multiple sessions and subjects and apply it to a subsequent session). To solve this problem, we have found that spherical registration with surface based smoothing and down-sampling yields the best results across both sessions and subjects. This cross-session registration procedure also allows us to collect and utilize more training examples for machine learning which also helps with the disparity in dimension and training examples and yields improved classification accuracy.

We want to decode an internal variable, decoding the presentation of a visual or audio stimuli are uninteresting for our purposes; we already know what stimuli we are presenting to the subject. Instead, we propose to decode the subject’s performance. This is something we don’t already know when we present the stimuli (though we can predict to a certain degree from the difficulty setting of the task). Furthermore, predicting a subject’s performance has obvious applications for training and therapy such as modulating difficulty to keep predicted performance on a specific trajectory.

In traditional cognitive neuroscience experiments, fMRI signals are averaged across repeated presentations of the same stimuli to boost signal to noise. The stimuli is highly controlled to ensure that the elicited cognitive state is the same (or nearly the same) across all presentations. However, since we don’t know *a priori* what the elicited internal cognitive state will be (by design; if we already knew the state then why are we decoding at all?) we must develop techniques that can leverage the temporal structure of the signal to deal with the signal to noise problem and improve decoding accuracy. Hidden Markov models have been used in a variety of fields to solve precisely this problem (refs).

# Methods

## Stimulus

## Psychophysics

Trained outside of scanner

Sigmoid fit to performance curves

Game tuned to provide maximum difference between easy, medium, and hard difficulties

## MRI

### Anatomy

### Inplane

### Functional

## Preprocessing

### Anatomy

Surface extraction and spherical template alignment (freesurfer reconall)

### Inplane

Skull strip and normalize (freesurfer reconall first stage)

Robust register to anatomy and save transform (freesurfer mri\_robustregister)

### Functional

Simultaneous slice-timing and motion correction within each run (nipy.SpaceTimeRealign)

Rigid body registration between runs aligned to frame closest to inplane in time (fsl MCFLIRT)

Boundary based registration to anatomy using extracted surfaces. Initialized with transform calculated from inplane (freesurfer bbregister).

Project onto extracted surface averaging between white and pial surfaces along surface normal. Spatially smooth along the surface (freesurfer mri\_vol2surf).

Project on to template icosahedron of order #. Spatial smoothing and icosahedron order linked by … (freesurfer mri\_surf2surf).

Wiener filtering in icosahedron space (weiner filter ref).

## Machine Learning

ANOVA feature-selection (ANOVA ref and sk-learn ref)

Cross-validation (cv ref)

SVM (SVM ref)

SVR (SVR ref)

### Filtering

Block filtering (neurometrics1 ref)

Hidden Markov model filtering (?)

### Within-Session

Compared volume, smoothed volume, surface, smoothed surface, and down-sampled icosahedron classification accuracy

### Within-Subject

Compared different smoothing and down-sampling icosahedron classification accuracy

### Across-Subject

Evaluated classification accuracy

# Results

## Psychophysics

Each subject with fits

## Within-Session Classification/Regression

With and without filtering

## Within-Subject Classification/Regression

With and without filtering

## Across-Subject Classification/Regression

With and without filtering

# Discussion

Discussion

# Bibliography

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