BrainReader: Effective Visualization of fMRI-based Movie Reconstruction

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***Abstract*—Previous work in decoding visual experiences based on fMRI activity has been successful in reconstructing images and movies that participants viewed inside an MRI scanner. Reconstruction is done by fitting a forward model that predicts fMRI activity across the brain in response to a set of movies. The model represents brain activity as a linearized function of visual information features that capture the structure of the movies (spatiotemporal Gabor wavelet filters). The forward model is then inverted and used to decode what the subject saw based on their brain responses to a testing set of movies. Decoding is performed by fitting a maximum a posteriori function to a large library of previously unseen movie clips. The top 100 decoded movie clips are then averaged or stitched together to produce a visualization of the decoding. Though the decoding is quite precise when measured quantitatively, these visualizations do not fully reflect its accuracy. We make the visualization more coherent by combining the decoded clips in several improved ways. First, we demonstrate the change in quality gained using weighted averaging. Then, we use HOG features to select a subset clips similar to the ground truth clip and SIFT flow to find an optimal path in time. Third, we use appearance morphing to visually align the path-arranged clips. Finally, we share the decoded movies resulting from the same stimuli across different participants in the experiment.**

***Index Terms*—fMRI, decoding, visualization, computational videography.**

I. Introduction

FUNCTIONAL magnetic resonance imaging, or fMRI, data can shed light on what individuals are looking at. Specific areas in the brain are known to react strongly to particular line orientations and locations. Using activation data from these centers, such fMRI data can “reconstruct” what an individual is seeing.

The Gallant lab from UC Berkeley has worked on this problem previously, demonstrating **VS: citation needed** that they can perform this reconstruction by averaging images from a training set. The top 100 images whose recorded fMRI profiles match most closely with the recorded data are simply stacked on top of each other to create output videos.

However, this type of visualization is very “messy”: while the quantified fMRI matches are quite strong, the output video stacks are misleadingly inaccurate. Using computational techniques, we improve the quality of these output videos.

II. Related Work

Our work relates to both basic image processing and video processing.

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III. Methods

Our processing pipeline takes as input two pieces of data for each second:

- The original clip stimulus presented to the subject
- The top 100 guesses (based on fMRI data) and their rankings

We first perform HOG feature extraction on both pieces of data and reject guesses whose HOG data does not match well with the original clip **VS: need to add something about how this is actually physically-based in the fMRI data... we should also look at how well the HOG features actually correlate to rankings. I’d assume we basically will be picking the top guesses, but I don’t know.**. We then extract SIFT features from the beginning and ending of each of the top guesses and calculate SIFT flow between them. Using cost back-propagation, we find the lowest-cost path through the remaining clips. **VS: Finally, we perform morphing between these clips using SIFT keypoints and output the final clip compilations.**

A. HOG Features

Histogram of Oriented Gradients (HOG) features roughly indicate edges in an image as well as the orientation of those edges. We use HOG features to ensure good *spatial* alignment of guess footage with the presented clip.

B. SIFT Features

Scale-Invariant Feature Transform (SIFT) features, often used in image recognition tasks, can give higher-level information about the contents of a scene. We use SIFT Flow **VS: citation needed** to

Appendix A
Proof of the First Zonklar Equation

Appendix one text goes here.

Appendix B

Appendix two text goes here.

Acknowledgment

The authors would like to thank...

PLACE PHOTO HERE

Natalia Bilenko Natalia is a cool grad student with purple hair that studies brains. She works in the Gallant lab in the Neuroscience department.

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Valkyrie Valkyrie is a grad student whose desk is covered in 3D printed stuff. She works for Bjoern Hartmann in the Berkeley Institute of Design.