Reconstruction of visual stimuli from voxel activations

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1 Introduction

Extracting visual information from brain activity, is a long-cherished goal of the neuroscientific community, which in recent years has become more and more realistic, using a combination of fMRI recordings, machine learning techniques and insight from biological models.

This project starts by first implementing a linear mapping (encoding) between the stimulus-pixel-space and the fMRI-voxel-space. As visual stimulus a flickering checkerboard disc is used.
By inverting this model (decoding), it is possible to reconstruct a visual scence. In this early simple mapping a perfect decoding is expected. Further possible models can be implemented, e.g. using a basis of gabor functions or correlation techniques.

Up to now we based the reconstruction on self-generated data, so the next step is to apply this to real data from actual fMRI experiments, where again the checkerborad stimulus disc was used.

In this setting the encoding was already performed by the brains inner processes, which challenges us with the question how to regain highly complex encoded visual data.

Since we know the presented stimuli at a given time point and the elicited brain responce in the voxel activations, we have a relation that enables us to train an encoding model. Then by inverting this, we can perform decoding and e.g. reconstruct the visual area, that causes the maximal repsonse of a voxel (or simply: reconstruct a voxels receptive field). From this a comparison between presented and reconstructed visual scence will give feedback about the models performance.

The focus in this second part lies in the determination of useful en- and decoding models. Besides the already mentioned inverse correlation techniques and the use of Gabor wavelets, also applying particle filtering could be a promising approach.

In order to process fMRI data the SPM12 toolkit and The Decoding Toolbox for multivariate analysis is used.

2 Methods and Results

2.1 Toy Data

The first approach to the problem of decoding visual stimuli from fMRI voxels in this lab rotation, was to avoid dealing with noisy real data and therefore toydata was generated. This has the great advantage that in the optimal case the algorithm has to perform perfectly and therefore is able to predict every input sector with a one-hundred percent accuracy from generated voxel data. The voxel data was computed by a matrix mapping:

$$V = MS \tag{1}$$

Where V is a vector with all voxel intensities , M is a mapping matrix and S a vector, which assigns a contrast value to every sector.

For the mapping matrix different designs were tested. The most basic case was$S = I$, so that every input sector intensity was mapped to a corresponding voxel with the same activation. Moreover, a random permutation mapping, meaning that every activation of the input is mapped to a random voxel position in the output, was used. Both mappings are bijective and therefore a perfect reconstruction can be found. Further mappings consisted of random mixing matrixes ($s_{i,j}\ N(0, 1)$)

2.2 Functional MRI Data

Explaining the experiment, and the use of the randomvector

The Checkerboard

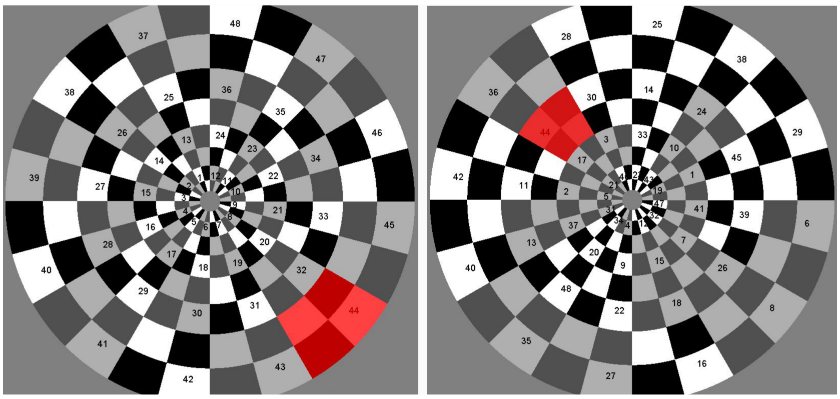

Figure 1: Scheme of experimental setup

Flashing checkerboards were presented to four subjects, whereby every subject had to complete eight runs with 100 different checkerboards each.Every new checkerboard configuration was taken from a predefined contrast matrix, with contrasts in four different intensities from 0 to 4, with the former indicating the sector to be switched off and the latter indicating the sector to be switched on with maximal intensity. The contrast matrix was the same throughout the whole experiment, but randomness was ensured by drawing one of ten predefined randomvectors for every new run. Every randomvector

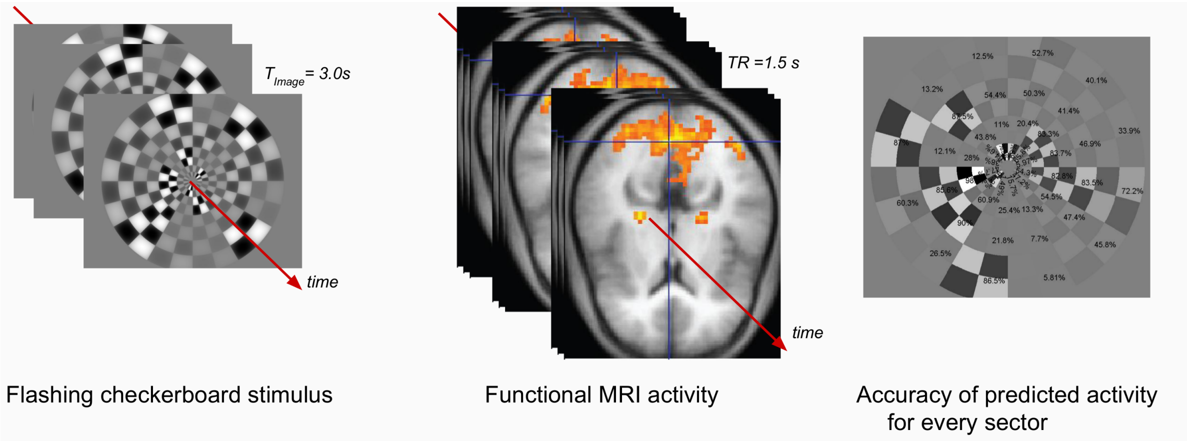

Figure 2

consists of a permutated indices array from 1 to 48, which maps every contrast value to a sector location. In order to get a consistent data structue, the contrasts for every run had to be remapped, which results in a contrast matrix with dimension 48 x 8*100.

The Experiment

To ensure the subjects attention to the viewing task, an additional fixation task was shown. For that three different Landolt Cs (fully closed, ring open to the left, ring open to the right) were presented in the center of the checkerboard. The subjects were asked to perform a left buttonpress in response to a Landolt C with an opening to the left, and respectively press right for an opening to the right side.

FMRI activity was recorded with a repetiton time $TR = 1500$ ms, the voxel sizes were 3 x 3 x 3 mm and the recorded data was slice time corrected and realigned.

Analysis for Subject 7

Plots as discussed (for different SL and Delays, confusion matrix, pearson r, acc. maps for visual cortex, boxplots for all segments, compare acc. means using t-test Explaining Different analysis types, (ROI, wholebrain, searchlight) using the TDT, Regression and Classification

Decoding L v R finger presses

A first decoding was performed on the basis of motor cortex activity in response to a left or right button press in the Landot C task. The goal was to predict a left or right press by training a classifier on voxel activites. Therefore a SPM model was set up using all available functional MRI data and using the times of a left vs. right button press as onsets. The general model was estimated using SPM, which results in beta voxel maps

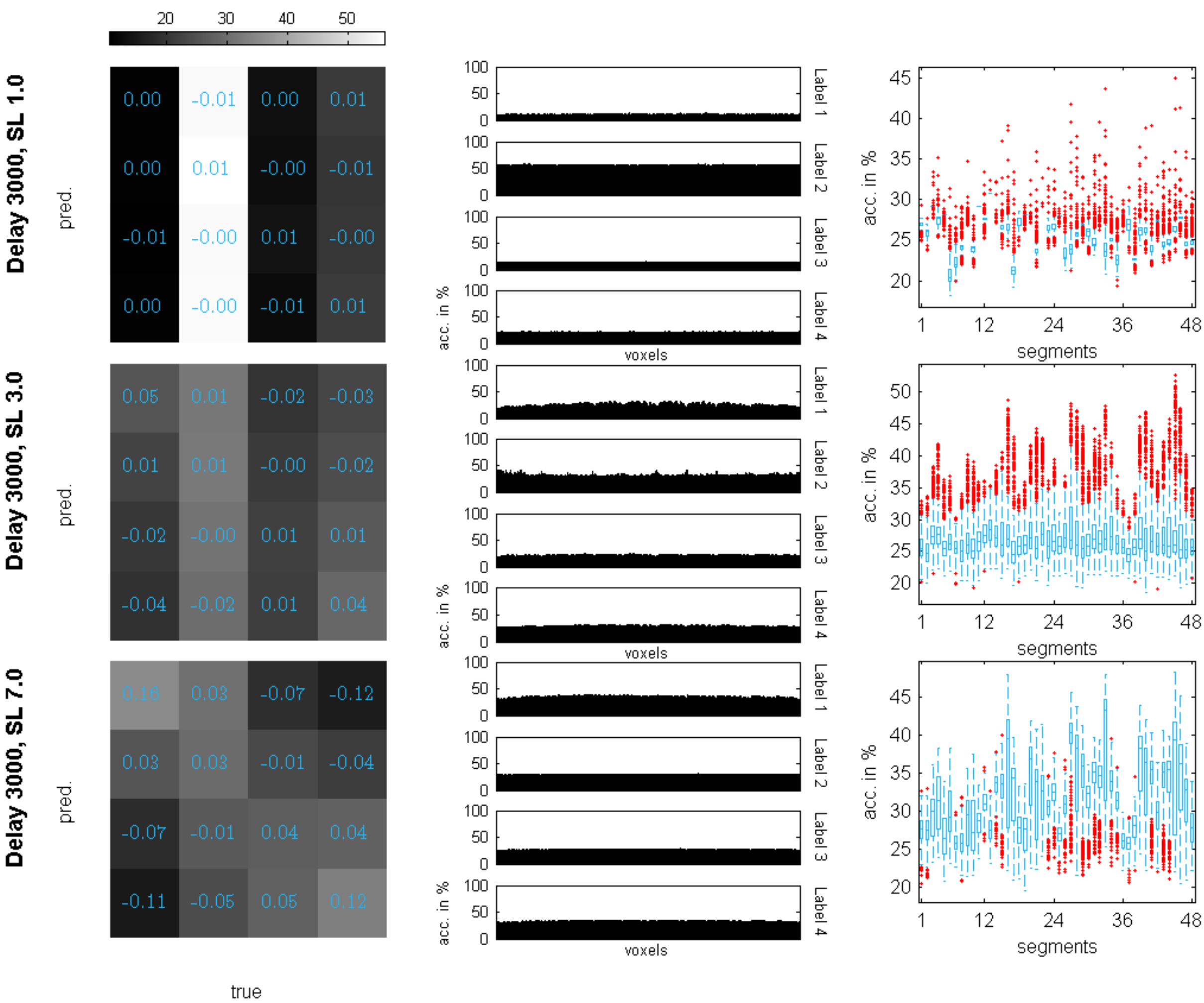

Figure 3: Left column: Confusion matrix for true vs. predicted labels (grey values) and overlaid correlation matrix (ligh blue)
Central column: Labelwise accuracies for every ROI voxel.
Right column: Boxplots for obtained accuracies in every checkerboard segment.

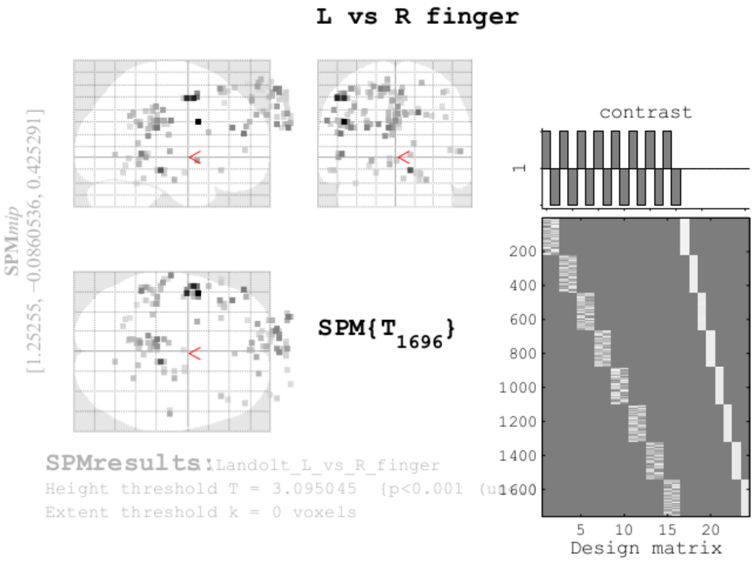

Figure 4: Significant voxels ($p < 0.001$) for the condition left vs. right finger presses.

for every regressor. These betas state how well the voxel activity can be estimated from the regressor time course.

Next, the estimated beta images are input to the TDT, which trains a classifier and predicts class affiliation to classes left button press or right button press. With this method an accuracy for every voxel was computed. In figure all voxels with accuracies ¿ 80.0 % are shown, with the maximal accuracy being 93.75 %, located in the left motor cortex. Another cluster of significant voxels with accuracies of 81.25 % and 87.50 % was present in the prefrontal cortex (not shown).

Looking at the results in Fig. 5 the voxels with the highest statstical significane are located over the left motor cortex, corresponding to the the location of the right hand in precentral gyrus hommunculus motor maps.

Retinotopic model

The same strategy of first specifying a SPM model and then using the resulting betas for the TDT, was applied to construct a model, which predicts the activity of every single of the 48 checkerboard sectors and results finally in an accuracy map for the reconstruction (see fig. 6).

The SPM model again was estimated using recorded voxel acitivities and the onsets of four different classes intensity 1, intensity 2, intensity 3 and intensity 4 for every sector. As before the duration for every intensity condition was 3000 ms.

Subsequently, the TDT was used to train 48 classifiers using a wholebrain searchlight analysis with searchlight radii of $r = 1.0,\ 3.0$ and 10.0, which were tested on an unseen

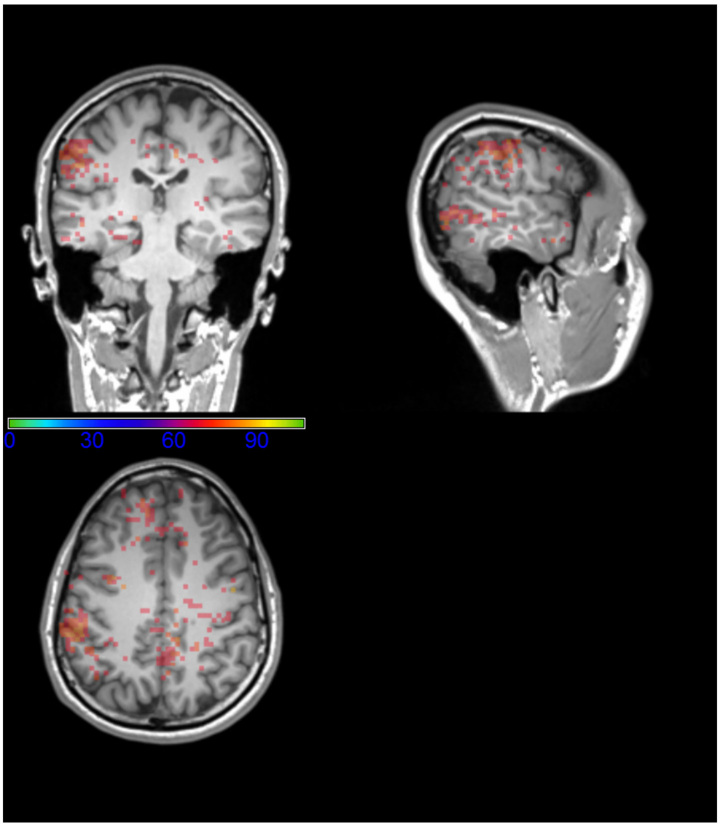

Figure 5: Decoding accuracies for left vs. right button presses

set of the data. From this predictions for class affiliation were obtained, compared to the real class labels and prediction accuracies could be computed. This resulted in 48 x $N_{searchlights}$ accuracies. The mean and maximal accuracy from every sector were plotted in Fig. 6.

It can be seen that by averaging over all accuracies from a searchlight analysis with $r = 1.0$, most effects cancel and the chance level of $100 \div 4$ classes $= 25\%$ is obtained. With increasing searchlight radius r the classifier is able to predict some sectors with above chance level, but at the same time some accuracies also fall significantly below chance level. This can be explained, because now spatial correlations between voxels are considered when chosing $r > 1.0$. By taking neighbouring voxel activities into account, the classifier can use more than one feature (level of voxel activity) to assign a class label.

Still, the main reason for the overall poor decoding accuracy is the fact that a wholebrain analysis contains considers all voxels, but most voxels are insensitive to a changing intensity in a sector of the visual field. Therefore, limiting the analysis space to the early visual cortex would be a rational next step.

Therefore, it is useful to not average over all searchlight accuracies, but to look at searchlights with maximal accuracy. This results in the lower plot in Fig. 6. Here, the smallest accuracies are 50.0 % for $r = 1.0$, 53.1 % for $r = 3.0$ and 37.5 % for $r = 10.0$, which are all clearly above chance level. The maximal accuracies are 84.4 % ($r = 1.0$), 84.4 % ($r = 3.0$) and 62.5 % ($r = 10.0$). This shows, that in the set of all voxel searchlights there are some, that perform reasonably good on the task.

Since these high accuracies could be caused by noise voxel information from anywhere in the whole brain, it again is reasonable to next use ROI masks.

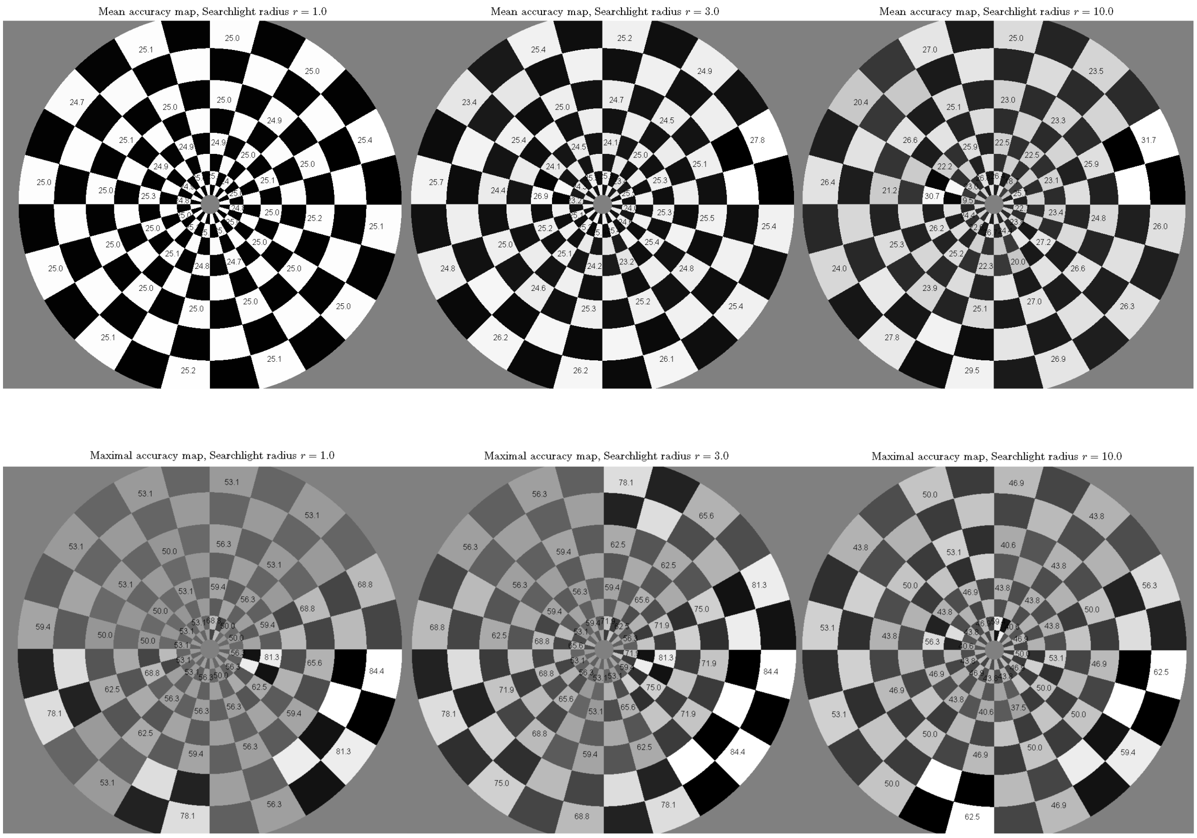

Figure 6: Upper row: Averaged accuracies over all voxels for increasing searchlight radii. Bottom row: Maximal accuracies for increasing searchlight radii