Decoding Directed Brain Activity in fMRI using SVM and GP

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Introduction

Associating a particular behavioral, cognitive or perceptual state to a specific pattern of fMRI voxels activity is still a challenge. Decoding of brain activity is usually performed using multivariate techniques [1] in highly controlled environments containing temporally separated states [2,3]. However, everyone is aware that this does not represent realistic information processing in the brain, where many stimuli are dealt with simultaneously or in short overlapping time periods.

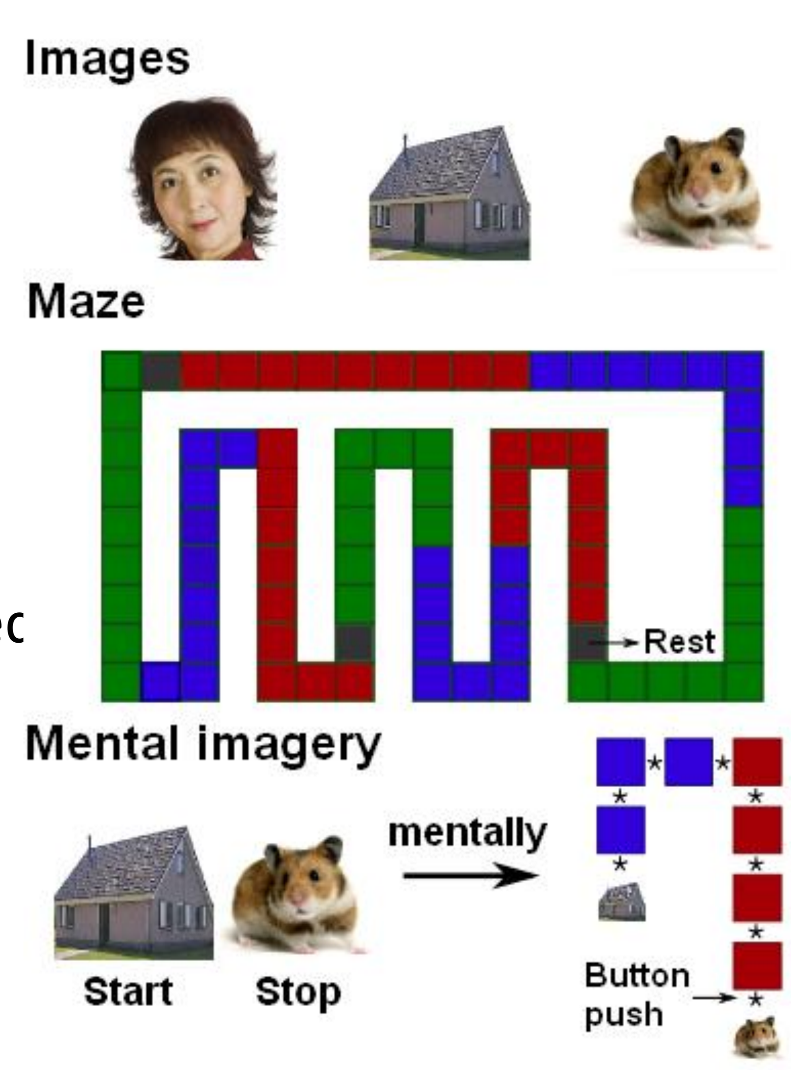
Aim: test a more realistic approach of brain information processing using complex data sets.

Methods

9 healthy volunteers
(age: 19-29, mean 24.9, 4 females)

2 fMRI sessions:
- Maze exploration: temporally controlled and balanced.
- Mental Imagery: complex data set since the number and the duration of events are user-definec Imbalances between categories.

Using 3 types of images (the 3 classes): Faces (F), Buildings (B) and Animals (A)



Preprocessing using SPM8.

Feature selection using a General Linear Model (GLM [4]) and/or Support Vector Machines (SVM, [5]). Classification using SVM or Gaussian Processes (GP, [6]). These techniques were combined into the following procedures:
- Procedure 1: GLM feature selection and SVM classification
- Procedure 2: GLM feature selection and GP classification
- Procedure 3: SVM feature selection and GP classification
- Procedure 4: GLM and SVM feature selection and GP classification

Accuracy measures using cross-validation (nested if needed) and an Error-Correcting Output Code approach (ECOC [7], table 1) to obtain multiclass predictions.

	SVM codewords			GP codewords		
	F-B	F-A	B-A	F-B	F-A	B-A
F	1	1	0	1	1	0.5
B	-1	0	1	0	0.5	1
A	0	-1	-1	0.5	0	0

Table 1: codewords of the ECOC approach, using either binary outputs (SVM) or probabilities (GP)

Results

For the exploration session, all procedures could significantly ($p<0.01$) classify the data from the 9 subjects.

For the mental imagery session, our results showed that 6 data sets out of 9 could be significantly modeled by either SVM or GP (figure). Procedures 1 and 4 performed significantly better in terms of overall accuracy than the others.

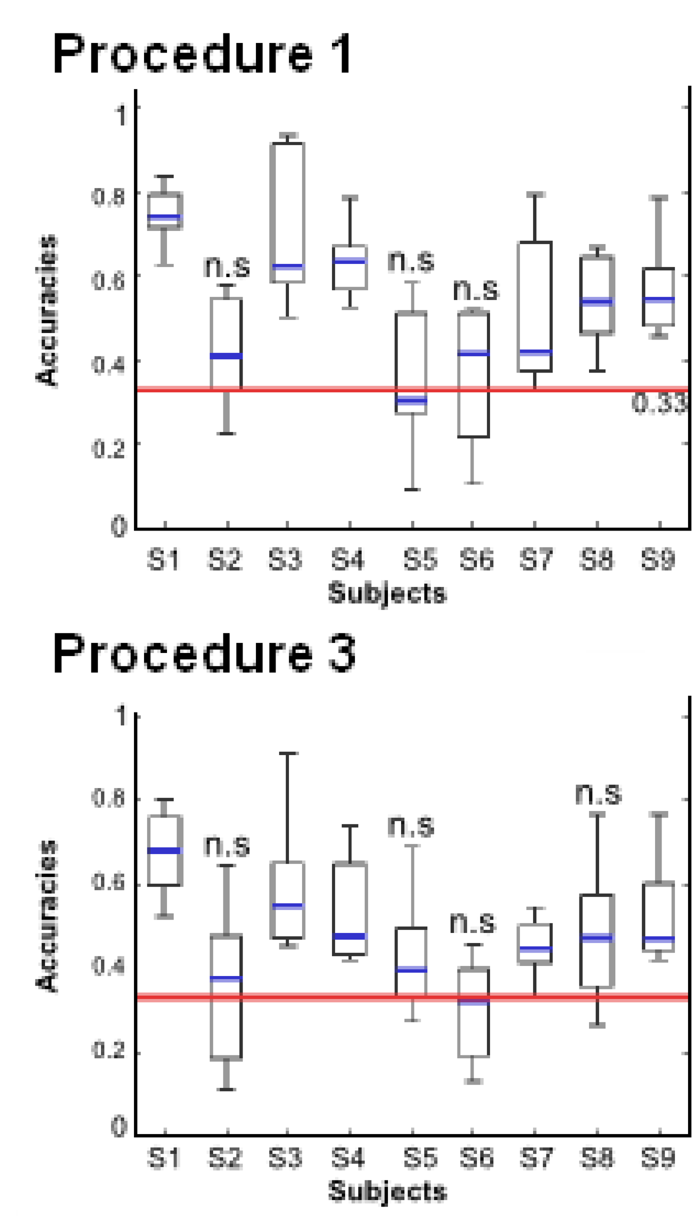
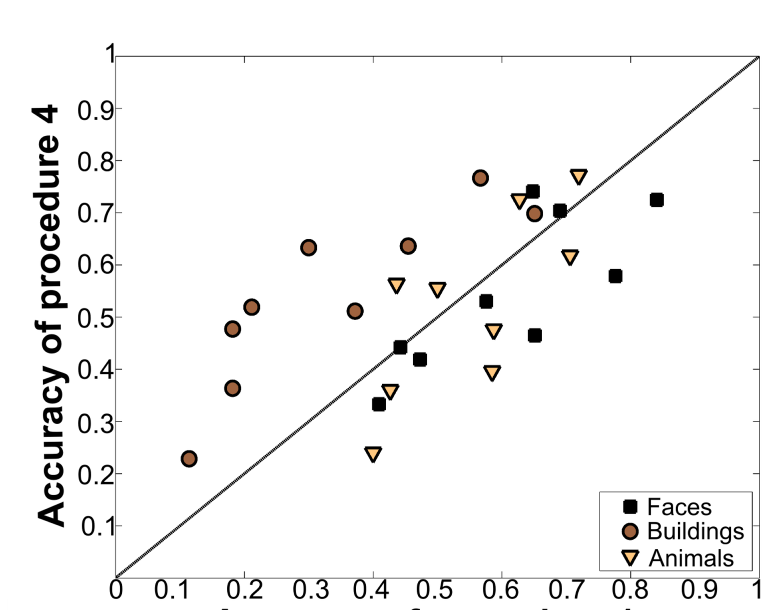
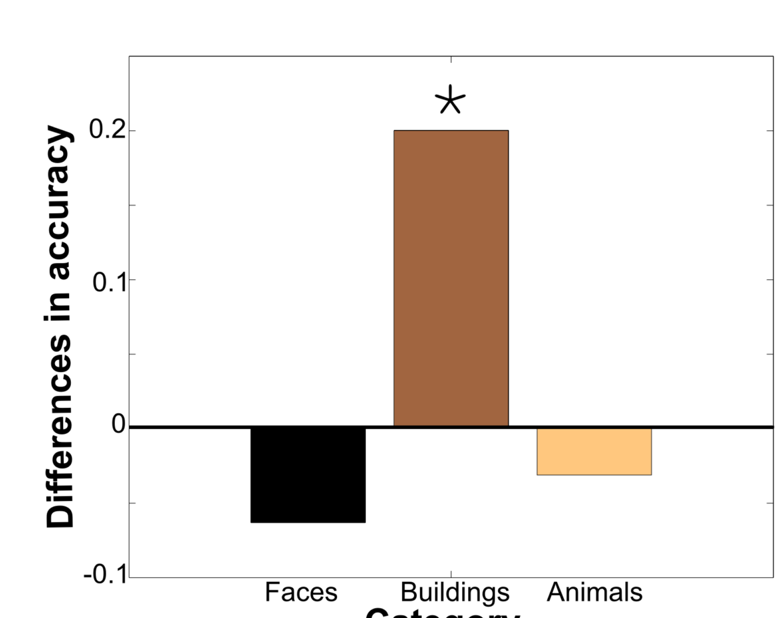


Figure: median accuracies and interquartile range for all subjects and procedures. Red line represents the 33 % chance level, while 'n.s' means not significant.

However, it was observed that GP better modeled the less represented class (namely the building class) than SVM, leading to significant differences in class accuracies between procedures 1 and 4.





We also noted that model accuracies tended to be related to the level of imbalances on the classification task, and to task performance of the volunteers. However, no significant correlation could be found between these measures (too small sample?).

Conclusions

On the strictly controlled exploration session, SVM and GP classification gave equivalent results: an accurate classification of the data from all subjects. On the other hand, the definition of the mental imagery session led to complex data sets, comprising more "random" activity linked to the subject's recalling activity and decision making process. Still, the best combinations of techniques were able to classify accurately the mental images from 6 out of the 9 subjects. The poor results of the 3 remaining subjects could be due to variable mental activity, too short mental event or unbalanced number of events per category.

References

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Acknowledgments

Belgian National Research Funds (FRIA-FNRS), the University of Liège and BIAL.

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