

SVM analysis of nicotine craving using functional MRI

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Introduction

Machine learning techniques offer a novel way of looking at brain imaging data and have recently been used increasingly in fMRI data analysis [1]. Recently, real-time capabilities have allowed such multivariate pattern analysis techniques to be used with fMRI to perform real-time brain-state classification [2]. Smoking addiction or nicotine dependence is a major health problem and nicotine craving can be a persistent and disturbing feature of such addiction. Studies have reported that nicotine dependence level of subjects is associated with greater BOLD fMRI activation [3, 4] and craving for cigarettes [5] in response to smoking cues. In this study, we try to analyze brain fMRI data of nicotine dependent subjects using support vector machines. We draw correlates between amount of craving and corresponding BOLD activation. This helps explain the neural mechanisms involved in craving and throws light on the possible application of real-time fMRI as a neurofeedback tool to enable self-regulation of nicotine craving.

Methods

Subject screening: Data was collected for 19 subjects. Several measures including expired CO level (at least 12ppm), number of cigarettes smoked daily (at least 10), Fagerström scores (at least 4) were considered to ensure moderate smoking and level of nicotine dependence. Subjects were scanned after overnight abstinence verified by measuring decrease in CO level on day of scan.

Acquisition: Bold functional images were acquired on a 3T GE scanner using T2*-weighted single-shot custom spiral-in sequence. (TR/TE/FA/FOV=2s/30ms/90°/22cm, 64x64 matrix, 40 axial slices of 3mm thickness).

fMRI paradigm: A paradigm was designed to present the subjects with images previously used in [6,7] that depicted smoking and non-smoking scenes. Two separate paradigms were created using blocks of smoking scenes interspersed with blocks comprising of non-smoking scenes. These were accordingly expected to elicit cigarette craving. (20s blocks, 5 pictures for 4s each, 16 repeats, with 4s static fixation image in between each block, 384s total time). A rear projection display and MR-compatible button-response pad was used. Subjects were required to rate each image (on a scale of 1 to 5) in real time depending on how much it made them crave cigarettes (1 suggesting least craving and 5 implying most craving). Two runs were acquired using these paradigms.

Analysis: Support vector machine classification (SVM) and support vector regression (SVR) analyses were done on these runs. Binary labels (0, 1) were used for SVM whereas labels based on the subjects' self-report of craving were employed for SVR. A model was trained on run 1 and then tested on a previously unseen run 2, and vice versa. The analyses were run on whole brain data using a linear kernel and default parameters in 3dSVM [8] package in AFNI [9]. Classification accuracy was quantified as the number of time points that were correctly classified by SVM and RMSE was calculated to quantify the goodness of fit of SVR predictions.

Results

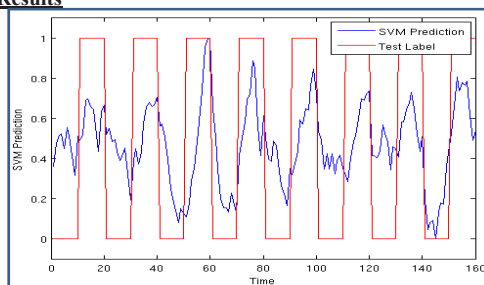


Figure 1. Plot of SVM prediction for 1 subject. (Class 0→non-craving and Class 1→craving)

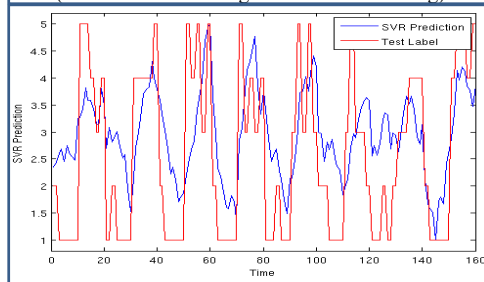


Figure 2. Plot of SVR prediction for 1 subject. (Label 1→least craving and Label 5→most craving)

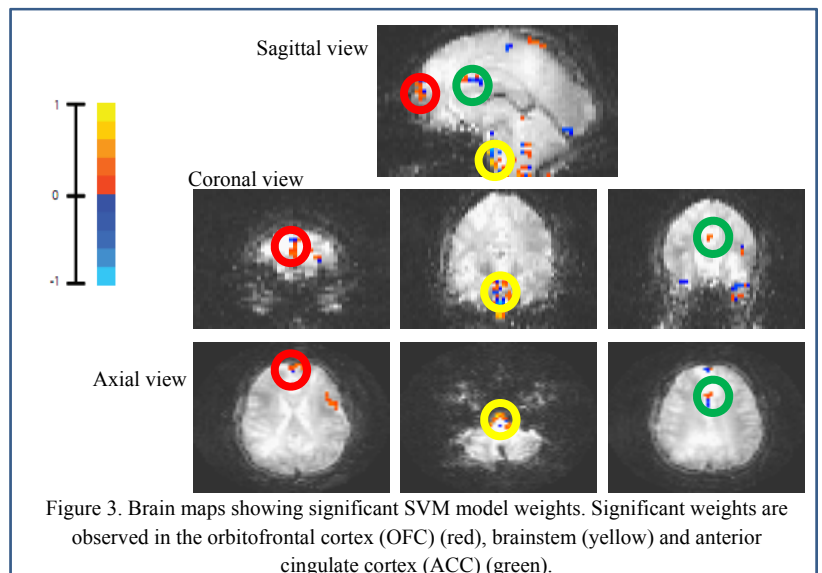


Figure 3. Brain maps showing significant SVM model weights. Significant weights are observed in the orbitofrontal cortex (OFC) (red), brainstem (yellow) and anterior cingulate cortex (ACC) (green).

Averaged over the 19 subjects, classification accuracy for SVM analysis was 67% when trained on run1 and testing on run2 and 66% when trained on run2 and testing on run1. Corresponding average value of RMSE for the SVR analysis was 0.36 and 0.38. As observed from fig. 2, the SVR prediction plot correlates with the user rating of craving and thus it is capable of predicting the craving level especially the sudden brief unexpected events. Since a linear kernel was used for classification, it is possible to generate a weight map as shown in fig. 3. Significant weights were observed in the orbitofrontal cortex, brainstem and anterior cingulate cortex consistent with previous studies on nicotine craving [10].

Conclusion

We have shown that machine learning can be used to track the craving level of a nicotine dependent subject by examining whole-brain fMRI data. After a model is trained, it is possible to exploit the fast nature of support vector testing and predict the subjects' brain state at every TR. These findings encourage the possibility of using neurofeedback mechanism to help subjects self-regulate their craving similar to that shown in [11].

References

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