Support vector machine classification of fMRI data in image and k-space domains

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INTRODUCTION

Multivariate pattern classification and prediction offers an alternative to standard univariate analysis techniques, and has recently been applied in MR imaging using support vector machines (SVM) [1], and used to attain real-time feedback [2]. The standard approach has been to use reconstructed image magnitude data. However, additional information may be contained in the image phase data [3]; and the ability to use the original k-space data might yield processing or acquisition advantages. This study explores applying SVM techniques both to the complex image data (magnitude and phase), and directly on the acquired k-space data.

METHODS

Data were acquired for four subjects on a 3 T GE scanner. T2*-weighted data was acquired using a spiral-in sequence (TR/TE/FA/FOV=2s/30ms/90/22cm, 64x64 matrix, 3mm slice thickness). A motor task paradigm was used, with alternating blocks of left and right hand finger tapping (20 s each condition per cycle, 8 cycles total, 320 s total time, two runs acquired).

SVM training and testing were done using the 3dsvm [1] in AFNI [4]. Six slices covering the motor cortex were used, with the images masked so only voxels inside the brain were analyzed. The image phase timecourses were processed to remove phase-wrapping. No other preprocessing was performed on the data. The SVM analysis was done on the image magnitude, image phase, and acquired k-space magnitude data separately.

RESULTS

Figure 1 displays the image space results. As expected, the significant SVM model weights are located in the primary motor and supplementary motor cortex, and the image magnitude data yields high prediction accuracy. In addition, the image phase results yield very high prediction accuracy and significant weights in the motor network.

As shown in Table 1, the prediction accuracy using the full k-space data is very high. Figure 2 plots the prediction accuracy using the inner and outer eighth of k-space. It is seen that using only the inner eighth still results in high accuracy, while using the outer eighth significantly reduces the accuracy.

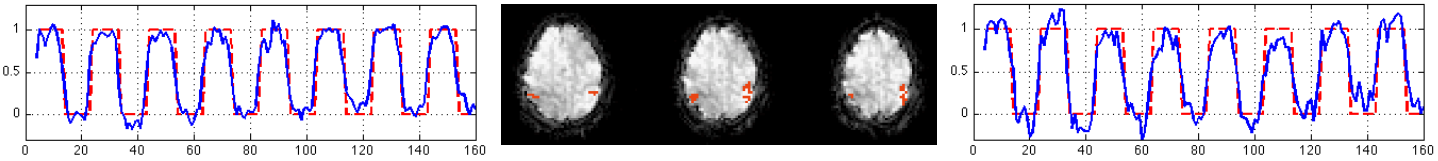

Figure 1. SVM results for image space data for a typical subject. **(Left, Right)** SVM prediction timecourses using magnitude/phase data, respectively. **(Center)** Overlap of the significant SVM weights in three slices for the magnitude and phase data.

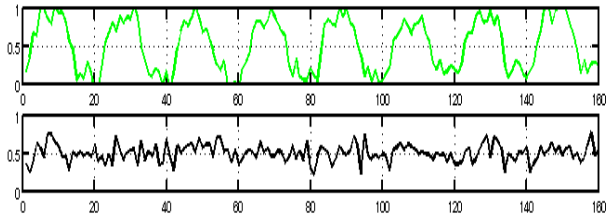

Figure 2. (Upper, Lower) SVM prediction timecourses using inner/outer eighth of k-space data, respectively, for a typical subject.

Subject	Image magn.	Image phase	K-space Magn.	K-space magn. Inner 8th	K-space magn. Outer 8th
1	0.99	0.97	0.98	0.98	0.74
2	0.95	0.87	0.92	0.83	0.67
3	0.93	0.95	0.91	0.93	0.63
4	0.95	0.99	0.97	0.96	0.65

Table 1. SVM prediction accuracy for all subjects.

CONCLUSION AND DISCUSSION

The prediction accuracy using only the image phase data was very high, and very comparable to the standard image magnitude approach. Thus, additional information is contained in the phase, and can be used to augment classification. It should be emphasized our accuracy was obtained with no additional preprocessing (e.g. physiological noise correction).

The prediction accuracy was also very high using the acquired magnitude k-space data. Thus, using k-space data for fMRI classification is feasible, eliminating the need for image reconstruction. Further, the ability to achieve high classification accuracy with only partial k-space coverage may enable alternative acquisition approaches (such as increased number of echoes).

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