Support vector machine classification analysis of Arterial Volume-weighted Arterial Spin Tagging (AVAST) images

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TARGET AUDIENCE – Researchers and clinicians interested in acquisition techniques that use a non-BOLD contrast, especially, arterial cerebral blood volume-weighted (aCBV) contrast. Also, experts interested in applications of machine learning techniques to brain state classification.

PURPOSE – Machine learning has been used increasingly for fMRI data analysis [1, 2, 3, 4]. This study presents an application of support vector machines (SVM) for temporal brain state classification using multiple acquisition techniques (BOLD, ASL and AVAST) and highlights the advantages offered by AVAST. Blood Oxygenation Level Dependent (BOLD) contrast is the most commonly used technique for acquiring functional images but it has certain deficiencies like low frequency signal drift [5], susceptibility artifact, etc. Standard perfusion-weighted Arterial Spin Labeling (ASL) addresses few of these shortcomings but lacks in signal to noise ratio (SNR) and temporal resolution. In this study, we employ a multivariate pattern analysis approach using SVMs to demonstrate how AVAST addresses these problems. Arterial volume-weighted arterial spin tagging (AVAST) is a variant of pseudo continuous arterial spin labeling acquisition (PCASL) technique [6]. By manipulating the tagging duration and TR, this technique ensures that only the arterial component of the signal is observed in the subtraction images. Thus, the AVAST scheme provides an aCBV-weighted signal with an activation detection sensitivity and temporal resolution comparable to BOLD while retaining the desirable properties of standard perfusion-weighted ASL techniques such as being a readily quantifiable physiological parameter.

METHODS –

Subjects and paradigm: Ten healthy control subjects participated in this study. They viewed a rear projection screen using mirrored glasses while being scanned. The paradigm involved displaying of alternating 30s blocks of flashing checkerboard (8Hz) and fixation cross. Subjects were instructed to perform self-paced unilateral right hand finger tapping when presented with the flashing checkerboard and rest when presented with the fixation cross. Two such runs were collected per subject. Details of the paradigm can be summarized as follows: (30s blocks, 5 cycles of alternating blocks of activation and rest; 300s total time).

Data acquisition: All functional images were collected on a 3T GE Signa Excite scanner. Images were captured using each of the three acquisition techniques (BOLD, ASL, AVAST) on every subject. To ensure that the steady state was reached, 4 dummy scans were collected at the start of each run.

BOLD- A single-shot gradient echo reverse spiral pulse sequence was used (TR/TE/FA/FOV=2s/30ms/90°/24cm, 64x64matrix, 11 contiguous slices)

Perfusion-weighted ASL- Images were acquired using a functional CBF scheme employing an off-resonance corrected PCASL technique [7] (TR = 4s, tagging duration = 2s, post inversion delay = 1.5s, TE = 4.5ms, 64x64matrix, BW = 125KHz)

AVAST- Firstly, a calibration scan was collected in order to find the optimal timing parameters (tagging duration and TR) for each subject as in [6].Using these parameters that were tailored for each subject, images were acquired using the functional aCBV scheme of AVAST (TR/tagging duration obtained from the calibration scan, no post inversion delay)

Preprocessing and SVM classification: All datasets were reconstructed, ASL data were surround subtracted and then analyzed using support vector machines. For SVM training and testing, libSVM [8] was used with linear kernel and C=1. At first, run 1 was used for training the classification model, whereas run 2 was used to assess the effectiveness of the model and then vice versa. Classification accuracy was defined as the fraction of time points that were correctly classified by the algorithm. Above procedure was repeated while ignoring 1, 2 and 3 transition points between rest and task states in order to examine if more robust models could be learned.

RESULTS – Figure 1 demonstrates that the mean classification accuracy obtained by AVAST is consistently better than that offered by ASL and almost equivalent to BOLD. Ignoring transition points improves the classification accuracy initially but plateaus for BOLD and AVAST, whereas, it deteriorates for ASL when 3 time points are ignored in each block. Figure 2 depicts select slices for a representative subject showing SVM weights in the motor and visual cortices as expected. The left-most column shows the 90th percentile of most significant weights for BOLD (blue) technique. The middle column shows the AVAST (green) weights superimposed on BOLD and the right-most column shows ASL (red) weights superimposed on BOLD and AVAST. It is observed that the significant weights show bigger and more robust clusters in the AVAST technique as compared to ASL.

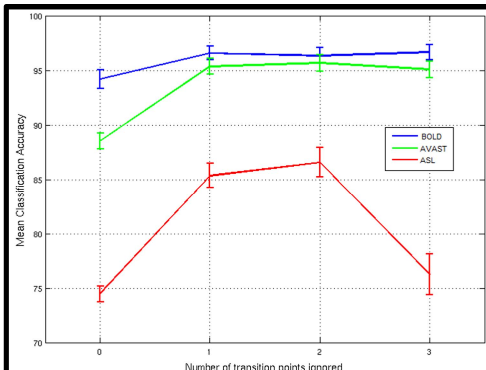

Figure 1. Mean classification accuracy over 2 runs of all 10 subjects for each acquisition technique (BOLD – blue, ASL – red, AVAST - green) against number of ignored transition points. The error bars depict standard error.

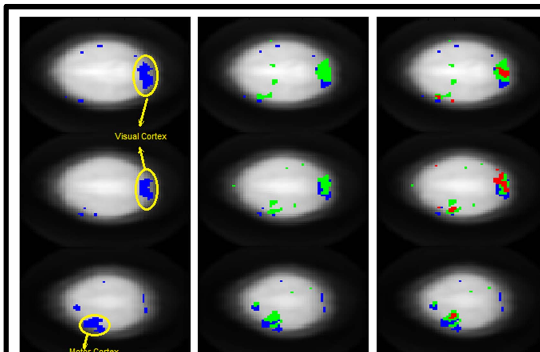

Figure 2. 90th percentile of most significant SVM weights for a representative subject for each acquisition technique. (BOLD – blue, ASL – red, AVAST - green)

DISCUSSION – Traditionally, perfusion-weighted ASL techniques suffer from low SNR and detection sensitivity. This variant of the standard PCASL, AVAST, affords improved detection sensitivity and also by taking advantage of the kinetics of the tag through the vasculature and tailoring the timing parameters to each subject, it allows for superior temporal resolution. Both these advantages allow for higher classification accuracies with machine learning techniques as shown.

CONCLUSION – This study presents promising results that promote the use of machine learning techniques for brain state classification of images acquired by using the AVAST technique. This technique might be used for dynamic fMRI experiments and real-time brain state classification studies.

REFERENCES – [1]Pereira, et al. (2009) Neuroimage, 45:199; [2]Mitchell, et al. (2004) ML, 57:145; [3]LaConte, et al. (2007) HBM, 28: 1033; [4]Mourao-Miranda, et al. (2005) Neuroimage 28:980; [5]Smith, et al. (1999) Neuroimage, 9:526; [6]Jahanian, et al. (2014) MRM ; [7]Jahanian, et al. (2011) NMR in Biomedicine, 24:1202; [8]Cheng and Lin (2001) http://www.csie.ntu.edu.tw/~cjlin/libsvm