Classification of ICA fMRI Data Using Suppot Vector Machines

X. Cui[1], M. Cole[2], L. Chang[3], T. Ernst[3], B. Stokes[3], and V. A. Stenger[3]

[1]Department of Electricla Engineering, Univeristy of Hawaii, Manoa, Honolulu, HI, United States, [2]Department of Medicine, John A. Burns School of Medicine, University of Hawaii, Manoa, Honolulu, HI, United States, [3]Department of Medicine, John A. Burns School of Medicine, Univeristy of Hawaii.Manoa, Honolulu, HI, United States

Introduction: Independent component analysis (ICA) of fMRI data is of current interest because it is data driven [1], requiring no a priori activation model. Unfortunately, visual inspection is still the most common way of determining meaningful IC's. Several techniques have been proposed to automatically classify IC's in fMRI [2]. In this work a technique based on 3D discrete wavelet transform (3DDWT) compression and support vector machine (SVM) classifiers is presented. We found that this approach could successfully classify IC's in a block-designed fMRI experiment at 3T.
Theory: SVM is a linear classifier that can group vectors into different classes according to their features [3]. 3D IC data can be compressed and then reshaped into a row vector becoming suitable for the SVM classifier. With sufficient training data, SVM can determine a linear hyper-plane that separates the data into two classes.
Methods: SVM classification was applied to fMRI data in 20 normal human controls performing three block-designed ball-tracking tasks (60 runs total) acquired at 3T using a standard EPI scan (TE=25ms, TR=2 sec, 42 64x64 5mm thick slices). The ball-tracking task consists of 60 seconds of tracking randomly moving balls in the field of vision and 60 seconds of non-tracking (i.e. resting state) [4]. 3DDWT and SVM processing was performed in Matlab. ICA was performed on all 60 subjects using the MELODIC tool in FSL [5, 6] generating approximately 20~30 IC's for each run. We chose the IC's with the largest variance related to the task and resting-state using visual inspection to test our method. Due to the large size of the data (64x64x64, Fig. 1 (a), per IC where the slice direction was zero padded to 64 elements), a 3DDWT technique was applied as a data compression approach to eliminate the redundant high frequency details [7]. The Haar wavelet is chosen as the mother wavelet. By 3DDWT compression, the final data size is cut to 8×8×8 (Fig. 1 (b)). The reconstructed 3D data (Fig. 1 (c)) and the normalized error (Fig. 4) show that the 3DDWT implementation produces minimal error.

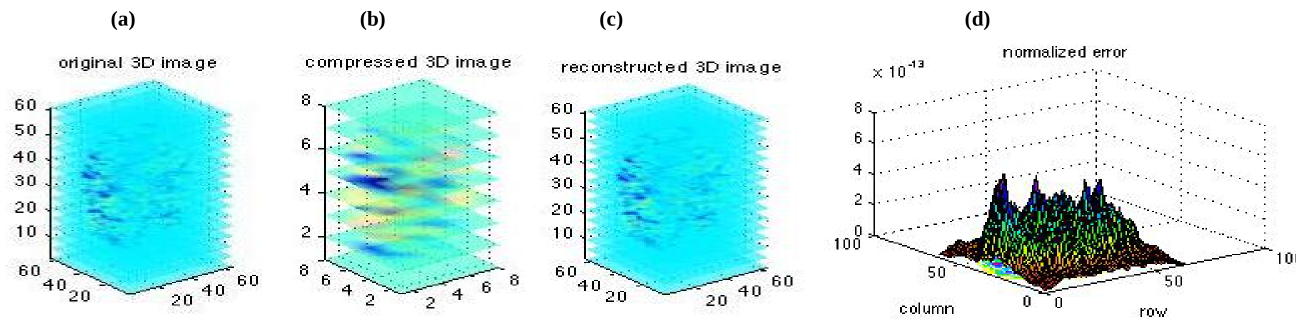

Fig. 1 (a) Original, **(b)** compressed, and **(c)** reconstructed IC's. **(d)** Normalized reconstruction error. Note the mean square error is on the order of 10^{-13}.
The compressed 8×8×8 IC's were reshaped into a row vector of 512 elements and then inserted into the SVM classifier. The SVM Matlab tool was downloaded from the webpage: http://svmlight.joachims.org/. We used 17 subjects (3 runs each or 51 total) as training data and 3 subjects (9 runs) as test subjects. The SVM training for classification consisted of (a) activation in bilateral posterior parietal cortex for the task-related model (Figure 2a) and (b) activation in the posterior cingulate cortex for the resting-state model (Figure 2b).

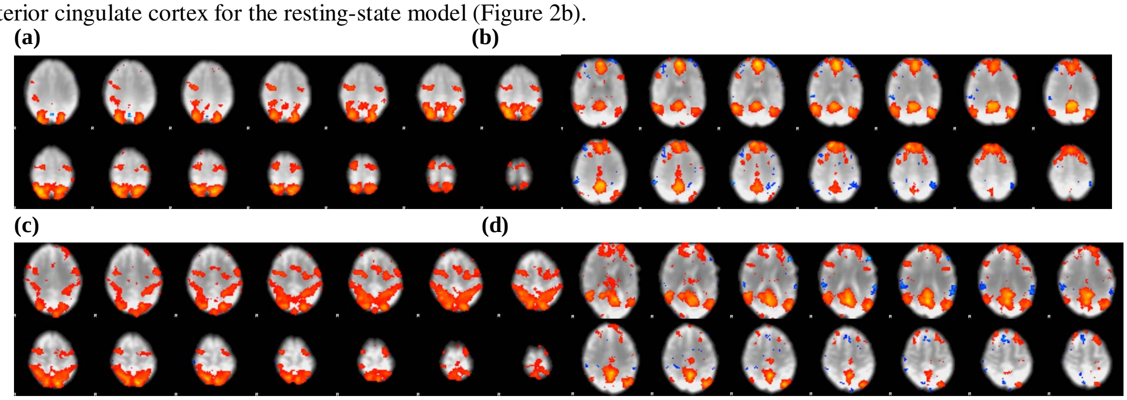

Fig. 2. (a) Task and **(b)** resting state IC's from a training subject determined by visual inspection. (c) Task and (d) resting state IC's from a test subject determined by SVM.

Results: The SVM technique correctly identified the task-related activation IC's in 8 out of the 9 runs and correctly identified 6 of the 9 runs for resting-state. Figure 2 (c) and (d) show example IC's from the test subjects that were correctly determined using the SVM approach.
Conclusions: A 3DDWT method was demonstrated to be a powerful technique to reduce computational complexity. In addition, an image processing method based on SVM is demonstrated to be effective and reliable for IC identification. This technique provides an objective means by which to identify independent components of interest. Future work using more a priori knowledge with the SVM classifier will group IC's into more specific classes revealing more subtle and/or complex neural processing.
References: 1. V. D. Calhoun, et al., *Proc. IEEE Workshop on ICA,* Nara, Japan, 2003. 2. Federico De Martino, et al., NeuroImage, 2006. 3. Christopher J.C. Burgers, A Tutorial on Support Vector Machines for Pattern Recognition. 4. Chang et al. Ann Neurol 2004 5. http://www.fmrib.ox.ac.uk/fsl/ 6. CF Backmann and SM Smith2004 IEEE Tran. Med. Imag. 7. Joyce Van De Vegte, Fundamentals of Digital Signal Processing.