WAVELET ANALYSIS OF 4D MOTOR TASK FMRI DATA

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ABSTRACT

We analyze the use of Haar wavelets in classification and clustering of 4D spatiotemporal fMRI motor data, comparing our results with previous studies that applied wavelets to motor task data as well as other techniques that have been previously applied to the same dataset, including voxelwise spatial k-means clustering and classification by subject based on time series analysis. Subject-based classification accuracies using wavelets reached 82% and distinct clusters emerged corresponding to differing anatomical regions of the brain, providing evidence that wavelets are an appropriate technique to use in both classification and clustering analysis of functional brain imaging data.

1. INTRODUCTION

Wavelets are useful spectral image analysis tools capable of exploiting significant spatial correlations between voxels and have been used with great success in shape recognition [1], time series analysis [2], musical analysis [3], and computer aided diagnosis [4,5,6], among other fields. While similar in principle, wavelets have a number of advantages over Fourier analysis, as demonstrated in the literature, including the ability to represent finite and discrete signals [2] and the ability to natively and easily accommodate multiresolution analysis [2,4].

In this paper, we apply four-dimensional Haar wavelet analysis to an fMRI motor dataset of 11 subjects periodically performing four simple motor tasks: touching their left index fingers to their left thumbs ("left finger-to-thumb"), squeezing their left hands ("left squeeze"), touching their right index fingers and thumbs ("right finger to thumb") and squeezing their right hands ("right squeeze"). Each task dataset consists of 120 images acquired at 2 second intervals and each image consists of 79x95x69 voxels. Previous experiments have been conducted on this dataset using analysis of variance (ANOVA) [6]. Here, we explore wavelet analysis in conjunction with k-nearest neighbor classification by subject and the k-means algorithm for clustering of voxels.

2. BACKGROUND

Wavelets are theoretically rooted in the Fourier transform, which expresses a signal, such as the spatial domain representation of an fMRI image, in terms of a linear combination of sines and cosines. The coefficients in this linear combination are obtained using the Fourier transform:

$$F(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t)\, e^{-ixt}\, dt$$

While Fourier analysis expresses a signal as a sum of sines and cosines, wavelet analysis permits decomposition into scaled and translated copies of a function known as the "mother wavelet", denoted ψ. This carries the additional advantage of localization in space as well as frequency. Furthermore, it allows us to speak of scale: multiresolution analysis may be performed simply by varying the scale parameter. These so-called "daughter wavelets" can be obtained from the continuous wavelet transform, which is given by the following formula:

$$\gamma(s,t) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} \psi\left(\frac{x-t}{s}\right)^{*} f(x)\, dx$$

Where * denotes the complex conjugate operation, s denotes the scaling parameter, t denotes the translation parameter, ψ denotes the mother wavelet, and f(x) denotes the original signal.

It is clear from the functional form that the wavelet transform yields not one, but an *entire family* of daughter wavelets derived from different scaling and translation parameters.

The Haar wavelet is a simple wavelet function belonging to the Daubechies family of wavelets. It is given by the following function:

$$f(x) = \begin{cases} 1 & 0 \le x < .5 \\ -1 & .5 \le x < 1 \\ 0 & otherwise \end{cases}$$

3. METHODOLOGY

We registered and normalized our dataset prior to analysis, clipping the top 5% of voxel intensities to prevent a small number of outlying voxels from influencing the overall normalization. We then applied a four-dimensional wavelet transform to the dataset by hierarchically applying four one-dimensional wavelet transforms, first along each of the three spatial dimensions, then across the temporal dimension.

We empirically observed that using the high-order sub-band coefficients in subject classification yielded far better results than the low-order sub-band coefficients, likely indicating that fine details in activation values have higher inter-subject discriminative power than the overall shape of the activation map. Therefore, we decided to use the concatenation of the high-order sub-band coefficients from each decomposition as a feature vector in k-nearest neighbor classification, which assigns a class to a data point based on the majority vote of the point's k-nearest neighbors. We chose to use the Euclidean distance as a classification metric and assessed the performance of our classifier using leave-one-out cross validation.

We preprocessed the dataset for voxel-wise classification and clustering by representing each voxel as a time-series, normalizing each series by calculating standardized Z-scores from the activation values, and smoothing each series through truncation of its high-order Fourier components in the frequency domain. Finally, we performed k-nearest neighbor classification and k-means clustering on the resulting time series data.

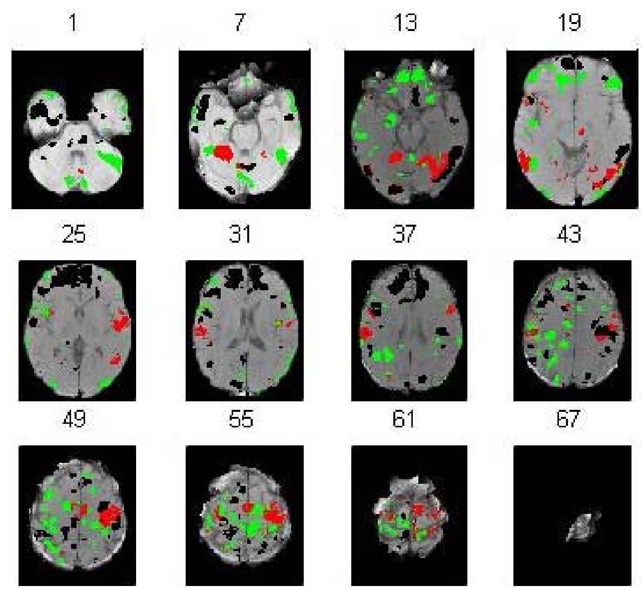
4. RESULTS

We first performed k-nearest neighbor classification by subject using Haar wavelet coefficients as features on a dataset of 11 subjects (classes), each performing four motor tasks consisting of sets of images on 120 time points containing 79x95x69 voxels. All four motor tasks were used in classification. The results of these experiments are shown in Table 1:

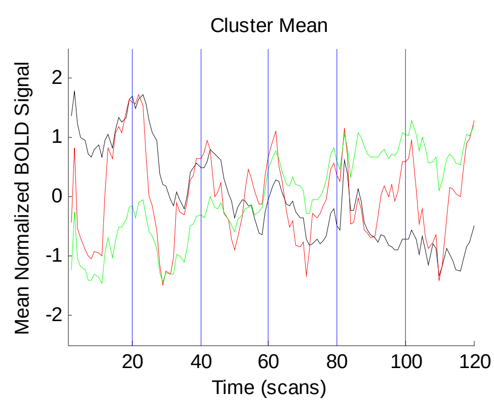
k	Accuracy
1	81.82%
2	81.82%
3	79.55%
4	81.82%
5	72.73%
6	75.00%

Table 1: Subject-based classification accuracies using Haar wavelet decomposition on all motor tasks.

We also performed k-means clustering on the time series of each individual voxel. The resulting clusters exhibit a close correspondence to anatomical structures of the brain, such as the frontal lobe and motor cortex, as illustrated in Figure 1:



(a)



(b)

Figure 1: (a) results of k-means clustering overlaid onto a brain atlas and (b) the associated time series.

The black cluster exhibits a high degree of correspondence to frontal lobe activity, while the red cluster corresponds to activity of the motor cortex. These associations were unsupervised, indicating that clustering may be capable of segmentation in fMRIs even without prior domain knowledge. Moreover, many interesting activation patterns can be seen in both space and time, such as motor learning in the frontal cortex (indicated by the negative slope of the black cluster over time) and a high degree of symmetric activation (contralateral activation in addition to activation of regions hypothesized to be task-related).

Finally, we performed voxel-wise k-nearest neighbor classification by subject in order to establish a basis for comparison of our methodology. We utilized summed Euclidean distance as a metric. Voxelwise classification accuracies were much lower than comparable wavelet accuracies, as expected, and are shown in Table 2. These results suggest that the properties of spatial and temporal locality exploited by wavelet analysis play a crucial role in the analysis of spatiotemporal motor task data.

k	Accuracy
1	50.00%
2	50.00%
3	52.27%
4	43.18%
5	45.45%
6	38.64%

Table 2: Subject-based voxelwise classification accuracies across all motor tasks.

5. CONCLUSION

Our experimental results demonstrate that wavelet analysis is a suitable approach for subject classification and clustering of 4-dimensional fMRI motor task data and yields an effective data preparation methodology for further analysis. Opportunities for future study include utilizing different wavelet functions, such as others in the Daubechies family, applying the techniques we have developed to other classification problems, such as task-related classification or classification of disease, and more detailed analysis of normal neural phenomena, such as motor learning.

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7. REFERENCES

[1] Eom, K, Shape Recognition Using Spectral Features, Pattern Recognition Letters 19:189-195, 1998.

[2] Chan, K, Fu, A. W, Efficient Time Series Matching By Wavelets, Proceedings of the 15th International Conference on Data Engineering, Sydney, Australia, March 23-26, 1999.

[3] Evangelista, G, Flexible Wavelets for Music Signal Processing, Journal of New Music Research, Vol. 30, no. 1, pp.13-22, March 2001.

[4] Ruttimann, U. E, Unser, M, Rawlings, R. R, Rio, D, Ramsey, N. F, Mattay, V. S, Hommer, D. W, Frank, J. A, Weinberger, D. R, Statistical Analysis of Functional MRI Data in the Wavelet Domain, IEEE Transactions on Medical Imaging, Vol. 17, no. 2, April 1998.

[5] Dinov, I. D, Boscardin, J. W, Mega, M. S, Sowell, E. L, Toga, A. W, A Wavelet-based Statistical Analysis of fMRI Data, Neuroinformatics, Vol. 3, no. 4, pp.319-342, December 2005.

[6] Mohamed, F. B, Tracy, J. I, Faro, S. H, Emperado, J, Koenigsberg, R, Pinus, A, Tsai, F. Y, Investigation of Alternating and Continuous Experimental Task Designs During Single Finger Opposition fMRI: A Comparative Study, Journal of Computer Assisted Tomography, Vol. 24, no. 6, pp.935-941, November 2000.