Activation Points Extraction and Noise Removal of fMRI Signal

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Abstract

In this paper we report a novel procedure to accurately estimate the power spectrum of the noise in the fMRI signal at a given voxel location; the estimated power spectrum is used to determine the threshold used as shrinkage or soft threshold to remove noise from both 1-D and 2-D fMRI signal. Spatial processing, such as clustering is done on the entire signal to isolate the BOLD response and further investigate whether the new positions and numbers of the activation points are different from that of theoretically anticipated positions for the experiment performed. It is confirmed that the anticipated positions of the processed fMRI data and the actual positions of the activation points of the original fMRI data coincide as expected theoretically for the experiment performed.

INTRODUCTION

Each activity a person performs is managed by a certain location of the brain. The location of a brain directly related to an activity can be visualized using images from functional magnetic resonance imaging (fMRI) instrument. These images are obtained using the changes between active and non-active state of location a brain. The image contrast obtained this way is very small, and fMRI instrument is so sensitive that it picks unwanted signals or noise, that induce distortions of the actual experimental signals, which can be interpreted as false brain activities. The objective of this paper is to remove noise or distortions, which are unrelated to the experimental fMRI signals. The method, local cosine is suggested to remove noise from fMRI data due to its decorrelating effect in a temporal domain.

The main sources of noise are not fully understood. A number of possible sources have been suggested, for example, slow phase variations in the MR images due to respiration movements, cardiac and other physiological processes, patient movement, and local changes in the magnetic field due to scanner instabilities. During fMRI image acquisition process, high frequency components like heart rate (0.6 –1.2 Hz) and respiration (0.1 – 0.5 Hz) are under sampled with typical repeat times (TRs) of 3 to 7s and can, according to Nyquist's theorem, be expressed as low-frequency (0.1 Hz) signal components or aliased higher frequency signals [1].

Due to the fact that Rician distribution is used in the physics of magnetic resonance and the Gaussian distribution in functional neuroimaging, the noise, in the blood oxygenation dependent (BOLD) response of an fMRI data, is both Gaussian and Rician distributed. For high signal-to-noise ratio (SNR) fMRI data, Rician distributed noise is symmetric, thus, can be considered as Gaussian distributed. For low SNR fMRI data, there is a difference between Gaussian and Rician distributed noise, i.e, an image with low intensity and Rician distributed has probability density which is asymmetric. It was further shown that the difference between two Rician distributed images is symmetric and Gaussian distributed. Since an fMRI BOLD response is the difference between two BOLD responses, the active and passive state, thus, the noise in the resulting BOLD response is symmetrically distributed, which is characteristic of Gaussian distribution.

To remove the noise, first, the noise is decorrelated and then the intensity of the noise is estimated statistically. Second, the estimated noise is removed from the fMRI data in a temporal domain adaptively. Real and simulated fMRI data is used to confirm that the method remove noise and preserve activities related BOLD response of an fMRI data. In simulation environment, both one-dimensional (1-D) time series and two-dimensional (2-D) images are used to test the effect of the suggested methods on the signal-to-noise ratio (SNR), and Mean-square-error (MSE), see Figure 2. In processing 1-D data, local cosine processing recovered the original SNR with minimal MSE and with no visual residual artifacts, see Figure 1. Compared to other processing methods, local cosine performed as anticipated, i.e., it extracted active points from a real fMRI data with minimal processing errors and increased SNR positively. In general, the SNR of signal-carrying coefficients has increased with respect to the original voxels, when cosine is used, thus improving the potential sensitivity of detecting the activation patterns buried in large noise.

After denoising, to extract the activation points related to the BOLD respose: first, to reduce the false discovery rate, clustering is performed in spatial domain based on optimal minimal cluster size obtained from Monte Carlo simulation for a user-defined confidence level to determine the minimum size of clusters with minimal false discovery rate. Second clustering on the real fMRI data is performed using Euclidean distance using the minimum cluster size information. In this work, it is shown that local cosine can recover a signal from a data with a noise that has intensity of any standard deviation away from the center of the data.

MODELING OF FMRI DATA

Overall, we need to model and remove deterministic components from the time series before proceeding with the statistical analysis. The fMRI signal $y_m(t)$ at point M in the brain is given by:

$y_m(t) = \square_m x(t) + (t)$ (eq. 3.1)

Where n(t) is stationary Gaussian noise, – $\square_m$ is a scalar that measures the strength of the response at the voxel M. When we process $y_m(t)$ using local filtering and the resulting equation will be:

$Cy_m(t) = C\square_m x(t) + Cn(t)$ (eq. 3.2)

where c is coefficient of local cosine. Note : $y_m(t)$ can be extended to accommodate 2-D. Equation 3-2 makes the noise uniform, i.e, N $(0,\square^2)$, throughout the fMRI time series. Once the noise is uniform, it is easy to remove it. During the noise removal process, the temporal behavior of the voxel time series is used to remove noise, i.e., the temporal domain decorrelates the noise. The noise level or standard deviation of the noise can be estimated and used in the noise normalization process to determine the coherent signal as described in Section 0.

BACKGROUND

Statistical Parametric Mapping (SPM) tool and many research works use Gaussian filtering to remove noise from an fMRI data. Gaussian filtering is low-pass filtering, that is being used traditionally to process fMRI data, but it can remove relevant detail information. Gaussian filtering requires a window or a kernel size to be derived from the fMRI data itself to avoid processing errors . The other most widely used methods are Fast Fourier Transform (FFT) and SPline, but FFT unable to identify sharp transient events that are similar to fMRI data,. SPline is FFT and wavelet based, its sharp frequency characterization makes a good fit to process an fMRI or time related signal [2] but it needs optimization [3].

Most of the existing literatures suggest performing both the analysis and filtering in the time domain or temporal domain, and after the analysis phase in the time domain, an inverse transform is applied to reconstruct an activation map from the coefficients that are designated as significant. While this reconstructed map is very useful for visualization purposes, it does not have a direct statistical interpretation, that is, the statistical parameters, such as, t or z values are computed in the time domain and there is no straightforward way to map the statistics to the spatial domain.

In this paper both statistical analysis and filtering are performed separately and such an approach helps optimize the detection of false positive activation points of the voxel time series.

METHODOLOGY - ESTIMATION OF NOISE AND LOCAL COSINE PROCEDURES

In the temporal domain, the whole signal become symmetrical distribution and mean and median coincide, thus $\mu = m\square$. In addition, we assumed fMRI noise to be μ centered at zero (0); thus, MAD can be linked, for a normal distribution, to the average standard deviation $\square(x)$ of a single observation x as $MAD(x) = \square\square(x)$ where $\square = 0.6745$. . Through out this work this relationship is used to estimate noise for 1-D and 2-D fMRI signal at each voxel location.

The DICOM data with activation points is collected form patients and transformed into AFNI [4] format. The signal from AFNI is processed as specified below and ported to AFNI for visualization and local cosine processed to determine the activation points in the brain and to compare and contrast the processed signal with other fMRI processing methods.

The steps used in local cosine processing are as follows: Note that for 1-D and 2-D fMRI data processing the same algorithms apply except that for 2-D each row and column is processed separately and then combined together.

Determine the cosine basis of the given fMRI data as follows:

1. Preprocess the fMRI data using folding operator equation, then determine the cosine basis.
2. Estimation of the noise level of the fMRI data from its distribution
3. Determine the best basis using Shannon entropy as implemented by Coifman-Wickerhauser[5] , which states:
    a. Start from the bottom of the decomposition tree and mark every thing
    b. Determine the entropy of each element of the tree, and then if the entropy of a parent node is less than or equal to the sum of entropy of its the two children, them unmark the children and mark the parent, otherwise leave the children marked, continue this way until you reach the top.
5. Remove the noise residue:
6. Reconstruction of the modified or filtered signal.
7. Go to step 1 and repeat the steps until the entire time series or all fMRI slices are processed
8. End

RESULTS

Figure 1

Figure 1 Graphical comparisons of processing 1-D data in simulation environment (Original Signal-to-noise ratio = 3.736)

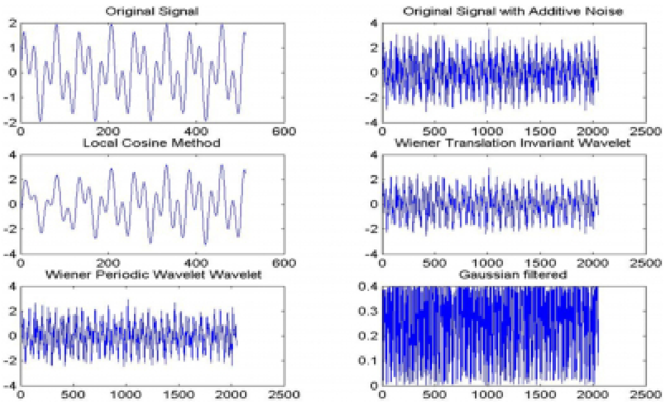


Figure 2

Figure 2: Quantitative comparisons of different methods to process a 1-D noisy data

Methods	MSE	SNR	Remark on Appearance
Local Cosine	1.3566	7.2702	Excellent
Wiener Translation Invariant	0.5695	3.7837	OK
Wiener Periodic Wavelet	0.6466	3.8681	OK
Ordinary Translation Invariant	4.8895	8.6568	OK
Ordinary Periodic	4.32404	9.0219	OK
Fast Fourier	1.6733	5.2924	OK
Gaussian Filter	4.2575	-13.2674	Not OK
Fractional Spline	1.67336	5.2924	OK

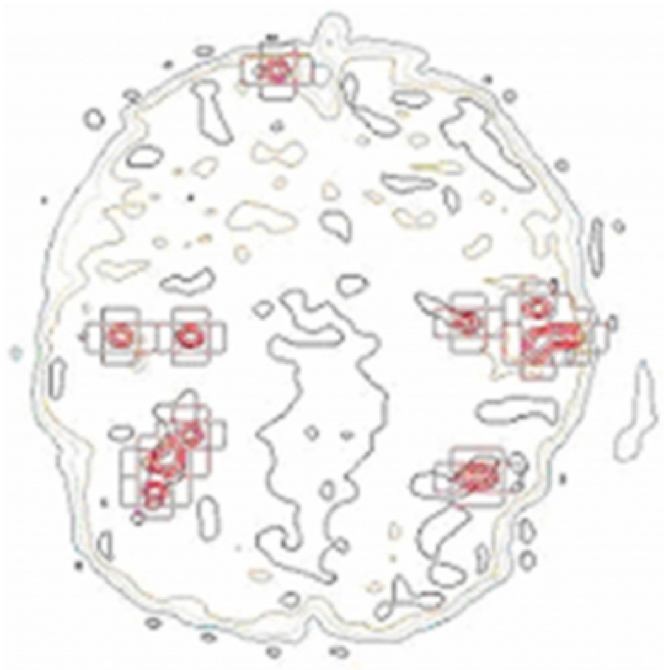
The results of processing fMRI data using local cosine are shown below. Both simulation and experimental real fMRI data are used to study the efficiency of the suggested methods. Both 1-D and 2-D simulated data with correlated and uncorrelated noises with known standard deviation is used to study the outcome of different algorithms. The 2-D simulation data uses an image with varying degree of standard deviation of noise generated in the laboratory. Figure 2 depicts the graphical comparisons For 1-D simulation data processing.

For 2-D processing, correlated and uncorrelated noise with known standard deviation is added to a 2-D image and the noise is estimated and then removed using local cosine, when the fMRI data is processed with known and estimated noise level, processing using the known noise level outperformed processed using estimated noise due to the fact that estimation takes into consideration the noise that was inherently present in the signal.

To eliminate false positive, Bonferroni correction, the simplest method to minimize false discovery rate, is considered too conservative for spatially correlated noise. In this report corrections based on modified Bonferroni [6] coupled with minimal number of voxels in a cluster from Monte Carlo simulation is used. Monte Carlo simulation determines the minimum number of voxels in a cluster given the confidence level. This approach, to control false discovery rate, is more powerful than Bonferroni correction. In this paper, local cosine based denoising and voxel clustering on the outcome of Monte Carlo simulation is used to control false discovery rate of the given fMRI data. Since true region of activation will tend to occur over contiguous voxels whereas noise has much less of a tendency to form clusters of activated voxels, clustering helps separate the noise from the true signal [7,8,9,10]. A cluster is formed using distance from the center of a voxels to nearest neighborhood to determine if a particular voxel should be added to a cluster. If the calculated euclidean distance between voxels is less than the specified distance, the voxel is included in the cluster, however, some voxels that are far apart may be included in the calculation and these voxels may belong to different functional behavior, to avoid the inclusion of voxels from different functional behavior, a single voxel width is used as connection distance with a Monte Carlo simulation for given confidence level = 0.05 to determine the minimum number of voxels in a cluster, assuming the underlying population of voxels intensities has normal distribution.

Figure 3

Figure 3: Cluster of Activation Points when the subject is finger tapping

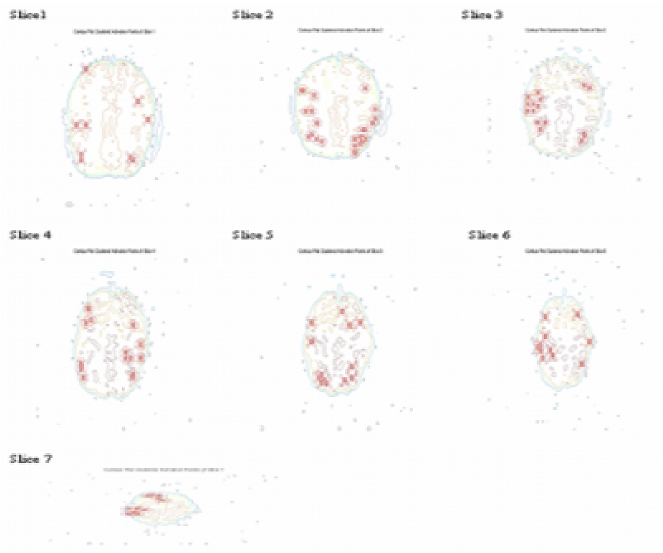


The brain processes different information in different way, for example, when the subject was instructed to process items according to their meanings (is the word hot or cold ?) or when the subject is instructed to perform bilateral finger tapping at a set of interval of time. The former task was associated with activations in a set of brain regions including left lateral prefrontal cortex (PFC) and left medial temporal cortex. The latter showed relatively greater activation in right and left PFC. In this experiment no comparison across subject is performed and an individual subject data is analyzed independently, and the subject was instructed to perform bilateral finger tapping as brain activation mapping of this action can be seen on both sides of lateral prefrontal cortex, and this finding, Figure 3 ,is consistent with theoretical basis of neural functions for a healthy individual, the complete result of the processing an fMRI obtained from a healthy person is shown in Figure 4.

The other most important thing to notice is, during the experiment, sometimes the well instructed subjects do all kinds of things in addition to the task they were asked to perform and this showed up in the fMRI images, as seen in Figure 4 interpretation of the results should take into consideration this kind of events. Furthermore, the best strategy is to mask the data to include only the areas or regions that corresponding to the activities in the brain.

Figure 4

Figure 4: Cluster of Activation Points when the subject is finger tapping



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