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ADAPTIVE DENOISING TECHNIQUE FOR ROBUST ANALYSIS OF FUNCTIONAL MAGNETIC RESONANCE IMAGING DATA

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Abstract- **A new adaptive signal-preserving technique for noise suppression in functional magnetic resonance imaging (fMRI) data is proposed based on spectrum subtraction. The proposed technique estimates a model for the power spectrum of random noise from the acquired data. This model is used to estimate a noise-suppressed power spectrum for any given pixel time course by simple subtraction of power spectra. The new technique is tested using computer simulations and real data for event-related fMRI experiments. The results show the potential of the new technique in suppressing noise while preserving the other deterministic components. Moreover, further analysis using principal component analysis (PCA) and independent component analysis (ICA) shows a significant improvement in both convergence and clarity of results when the new technique is used. This suggests the value of the new technique as a useful preprocessing step for this type of signals.**
Keywords – **fMRI, signal denoising, PCA, ICA.**

I. INTRODUCTION

Functional Magnetic Resonance Imaging (fMRI) provides a valuable noninvasive tool for investigating brain function. It localizes brain activity during mental or physical activity by detecting the corresponding increase in average cerebral blood oxygenation or cerebral blood flow [1]. To observe these hemodynamic changes, rapid acquisition of a series of brain images is performed. The sequence of images is analyzed to detect such changes and the result is expressed in the form of a map of the activated regions in the brain.

Classically, most of fMRI studies were conducted using the so-called block design approach, whereby two sets of data are acquired. First, a number of frames are acquired while the subject is at rest or under some baseline condition, then another set is acquired during the stimulus [1]. This pattern is repeated for a number of cycles in order to improve SNR, which would otherwise be quite low. Recent advances in both data acquisition and analysis have improved the temporal resolution of fMRI and made it possible to observe transient hemodynamic changes with reasonable accuracy. A good example for that is a new experimental design, similar to that of evoked-response potential (ERP) protocol, called single trial or event-related fMRI. In this new design, the subject receives a short stimulus or performs a single instance task while the resultant transient response is measured [2]. ER-fMRI offers many advantages over block design that include versatility, investigation of trial-to-trial variations, extraction of epoch-dependent information and direct adaptation of the methods used for ERP to fMRI [2]. The main drawback of ER-fMRI is the degradation in signal to noise ratio (SNR) due to the transient nature of the response. As a result, such studies now include epoch averaging. Nevertheless, this comes at the expense of suppressing the information about intra-subject variations related to psychophysiological function with each execution of the task. Therefore, a processing method that can be used to suppress noise in the acquired data would be very useful to reduce the experiment duration and preserve the information within the acquired data.

Several methods of data analysis have been used to process the fMRI raw data. The ultimate goal of such analysis is to try to separate signal components due to true activation, physiological fluctuations and random noise. The latter two components are considered as nuisance and must be removed for correct results. Among the most powerful techniques that can be used to separate signal components are those based on blind source separation such as principal component analysis (PCA) and independent component analysis (ICA). These techniques decompose the signal sources into either orthogonal components (PCA) or more generally independent components (ICA). According to the assumptions of both techniques, the number of independent signal components must be less than or equal to the number of signals to be analyzed. Otherwise, the separation of components yields incorrect results or even may not converge at all as in ICA. Unfortunately, this condition is not satisfied in fMRI data sets. Given the general assumption of uncorrelated noise, the number of components of random noise alone is equal to the number of signals. The total number of components has to add the number of components due to physiological fluctuations as well as the activation components. As a result, the use of PCA and ICA based techniques may not yield useful results in this case. Therefore, a technique that suppresses random noise or removes some of its components would be rather useful for making the use of PCA and ICA more robust for clinical practice.

In this work, we study the problem of reducing the random noise while preserving the other deterministic components in fMRI signals. A new adaptive technique is proposed based on spectrum subtraction. The theoretical analysis of the new technique and the implementation details are presented. The new technique is tested using computer simulations as well as real data and the performance is analyzed. Finally, the value of the proposed method as a preprocessing stage for PCA/ICA techniques is demonstrated.

II. THEORY

Generally speaking, the fMRI temporal signal can be modeled as the summation of the true activation signal, a physiological baseline fluctuation component, and a random noise component. The physiological baseline fluctuation component can be considered as a deterministic yet unknown signal. Therefore, we will consider a model that is composed of the sum of one deterministic component d(.) incorporating both the true signal and the physiological noise and an uncorrelated stochastic component n(.). That is,

$$s(t) = d(t) + n(t). \quad (1)$$

Since these two component are assumed independent, the corresponding power spectrums are related by,

$$P_{ss}(\omega) = P_{dd}(\omega) + P_{nn}(\omega), \quad (2)$$

where cross terms vanish because the two components are assumed uncorrelated. Hence, an estimate of the power spectrum of the deterministic component takes the form,

$$P_{dd}(\omega) = P_{ss}(\omega) - P_{nn}(\omega). \quad (3)$$

That is, the signal power spectrum is obtained by spectrum subtraction of the noisy signal and noise power spectra. In order to compute the deterministic signal component from its power spectrum, the magnitude of the Fourier transform can be obtained as the square root of the power spectrum. The problem now becomes that of reconstructing the signal using magnitude only information about its Fourier transform. Several techniques can be used to do that. The one used for this work relies on an estimate obtained from the phase of the Fourier transform of the original signal. Hence, the Fourier transform of the processed signal can be expressed as,

$$D_e(t) = P_{dd}(\omega)^{1/2} \,.\, \mathrm{Exp}(j\ \mathrm{Phase}(S(\omega))). \quad (4)$$

The enhanced deterministic signal is just the inverse Fourier transform of this expression.

III. Methods

A. Adaptive Noise Model Estimation

In fMRI, the acquired data set usually contains large areas of background and areas without activation. The time courses of pixels within such areas can be used to estimate a suitable model for the noise power spectrum. In our implementation, only background pixels (defined by simple intensity masking of the images) were used. Two methods can be used to compute an estimate of the power spectrum of noise using parametric and nonparametric approaches.

In the parametric approach, a noise model is assumed and the model parameters are estimated from the data. The power spectrum is subsequently calculated from the model. In the case of fMRI data, such model can be assumed as a zero-mean white Gaussian noise. Consequently, the power spectrum can be simply obtained as a flat curve with magnitude equal to an estimate of the variance of the background areas. On the other hand, the nonparametric approach does not assume a particular model for noise. The averaged periodogram estimate for the noise power spectrum is obtained directly from the pixel time courses of background areas. Since the number of pixels in such areas is expected to be large, the variance of such estimate is expected to be very small.

The difference between the two estimation approaches is that the parametric technique models the Gaussian random noise component of the original signal, while the nonparametric technique may also include other components such as global baseline variations. The selection of which to use depends on the type of subsequent analysis. In this work, we present the results from the parametric approach to make the analysis of the results consistent in comparison and to keep the baseline variations in the processed data to assess the performance of PCA and ICA in estimating such components.

B. Signal Power Spectrum Estimation

Since the proposed technique is applied to a single time course at a time, the periodogram estimate of signal power spectrum is expected to have a rather large variance [3]. As a result, the subtraction of power spectra in (3) may contain negative values in practical implementations. This causes a problem in trying to compute the square root to recover the processed signal. A simple approach to overcome this problem is to replace all negative values in the subtraction results by zero [3].

C. Statistical Noise Removal

Given the nature of the original signal, we observe that the variance in the power spectrum estimate may only result from the random component. Since the expected value of the noise variation is known from the derived model and given the statistical characteristics of the periodogram estimate, we can express the noise at each of the power spectrum frequency bins as a Gaussian random variable with mean and variance both equal to the noise model [3]. As a result, the subtraction in (3) would effectively remove only a part of the noise power spectrum. In other words, the upper half of the Gaussian distribution would still remain in the processed signal.

To solve this problem, a slight modification to the technique is added to allow direct control over the extent of noise removed. The modified equation takes the form,

$$P_{dd}(\omega) = P_{ss}(\omega) - \alpha \,.\, P_{nn}(\omega). \quad (5)$$

Here, the factor α is added to control the confidence of noise removal. This problem can be expressed in the form of a statistical z-test where the threshold α controls the p-value of the test. That is, the larger the value of α, the less the probability that the output power spectrum contains a noise component. On the other hand, increasing this value would increase the likelihood that some parts of the signal may also be removed. Therefore, the selection of the value of α is useful to fine-tune the results of the new technique. Several optimization criteria can be used to select the value of this parameter. An example of these is the use of entropy based objective function optimized over the autocorrelation function of the difference between the original and processed signals for different α values. This favors the values of α that give an autocorrelation function with narrow extent around zero and of minimal side peaks. This tends to preserve the components of the true signal, which give rise to periodic peaks in the autocorrelation function. In this work, we used a fixed value of this parameter that is equal to 1 to make it easier to compare the results and assess the improvement after using this technique as a preprocessing stage.

D. Analysis of Results Using PCA and ICA

To show the improvement in using PCA and ICA on the processed signal, the new technique is applied to process all pixel time courses in the acquired data set independently and then the processed data set is used for subsequent PCA/ICA. The PCA/ICA techniques were performed using a Matlab (Math Works, Inc.) program [4]. The goal of this analysis is to assess the performance of the new technique in enhancing the results of PCA and ICA and stabilizing the convergence characteristics of the ICA. Moreover, the difference signals between the original and filtered data sets were also analyzed using these techniques. This helps verify the absence of signal components within this discarded part of the original signal.

IV. Experimental Verification

The proposed technique was verified using computer simulations as well as actual data from a human volunteer. The computer simulations were performed in a similar fashion to [2] whereby a computer generated event-related fMRI activation signal was added to an actual baseline data set. The baseline data were collected on a healthy human volunteer using an EPI sequence (TE/TR=25/500 ms, FOV= 20cm x 20cm, slice thickness=5mm, images 640) on a Siemens Magnetom Vision 1.5T clinical scanner. The number of epochs was 8 and the length of each epoch was 64. The generated activation was designed to include inter-epoch variations in both the magnitude and width of the activation signal in order to test the performance of the new technique in preserving such variations. The overall standard deviation of the generated activation was varied to test the performance under different values for the signal-to-noise ratio (SNR) [2].

The actual data were obtained from an event-related fMRI study performed on a normal human volunteer using a Siemens 1.5T Magnetom Vision clinical scanner [2]. In this study, an oblique slice through the motor and the visual cortices was imaged using a $T2^*$-weighted EPI sequence (TE/TR=60/300ms, flip angle=55°, FOV=22cm x 22cm, slice theckness=5mm). The subject performed rapid finger movement cued by flashing LED goggles. The study consists of 31 epochs with 64 images per epoch. Temporal data from only 8 epochs of pixels in both the motor and visual cortices were processed using the new method and compared to the average of all epochs. The PCA and ICA techniques were applied to decompose the signal into its basic components. Both techniques were used to process time course signals before and after the new technique is applied on pixels within a window selected by the user. Moreover, the difference signals were also analyzed from the same window.

V. Results and Discussion

The results of applying the new technique to process computer simulated fMRI data are shown in Fig. 1 for SNR values of 1.0 and 0.5. As can be observed, the noise in the original data was suppressed significantly in the output and the difference signal appears free of signal components. In Fig. 2, the proposed technique is used to process real fMRI data from two activated pixels. The results look dramatically improved compared to the original. In fact, they appear even less noisy than the result from averaging while maintaining the signal structure unaltered. We also notice that the baseline variations also remained unaltered as a result of the use of the parametric approach for our noise model. Again, the difference signals appear to have no signal components. In Figs. 3 and 4, the results of applying the PCA and ICA techniques before and after processing with the new technique are presented. The figures show the first four components of each. The results appear very noise before applying the new technique in both methods. The results after it was used appear significantly clearer. We notice that the baseline variation component now appears in the ICA results, which was not present in the analysis before denoising. Moreover, severe instability was observed when using the ICA iteration on noise data. In fact, the analysis of the difference signal using this method never reached convergence in any of our experiments. This supports our hypothesis of the need to remove noise components to make the number of components less than the number of signals. Also, this shows that the proposed method was indeed successful to remove such components without affecting the true signal form.

The results of using the new technique suggest that it has the effect of robust removal of random noise while preserving deterministic signal components. Because it relies on subtracting the noise component, it does not affect independence of data points within the time course. The technique also has a very small computational complexity. It also has the advantage of being adaptive with very few assumptions about the noise model and no assumptions about signal. Finally, it provides statistical control over noise removal using a single parameter. The results indicate that the new method enables robust use of PCA and ICA. The limitations of the new technique include the fact that noise in the phase component is not removed and that spectrum clipping may occur due to large variance in power spectrum estimate from periodogram without averaging.

VI. Conclusions

A new signal denoising technique was proposed for fMRI signals. The method is adaptive and simple to implement while offering a substantial improvement of signal to noise ratio. The new technique was demonstrated for computer simulated and real data and also shown to improve the performance of PCA and ICA in analyzing fMRI data sets.

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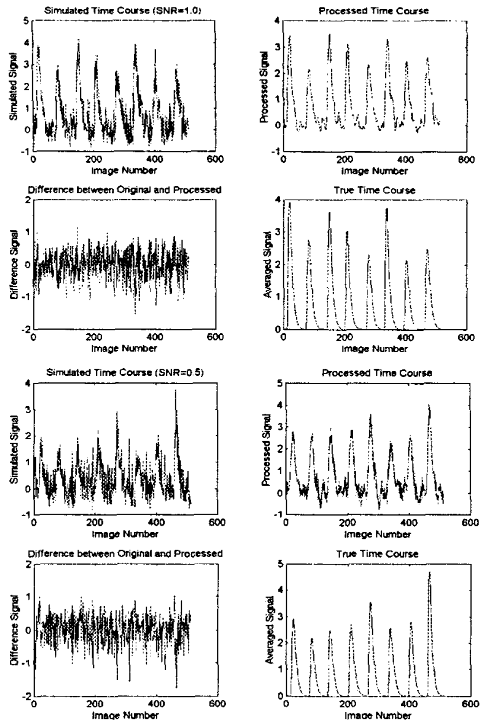

Figure 1: Results from simulations at different SNR values.

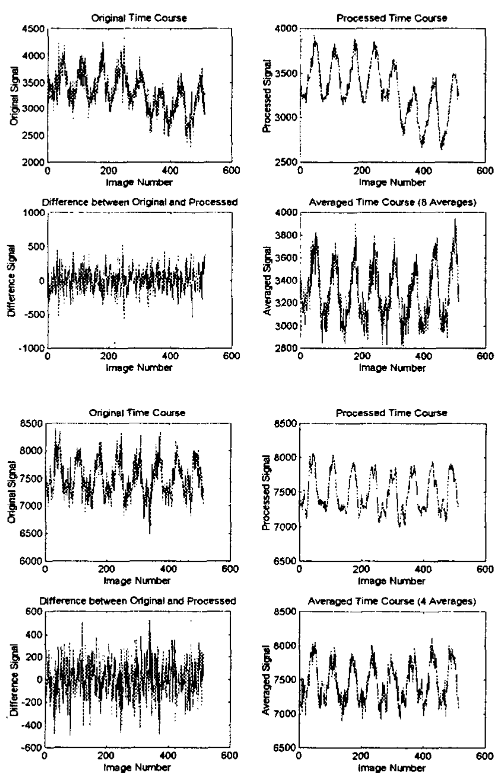

Figure 2: Results from actual data for two pixel time courses.

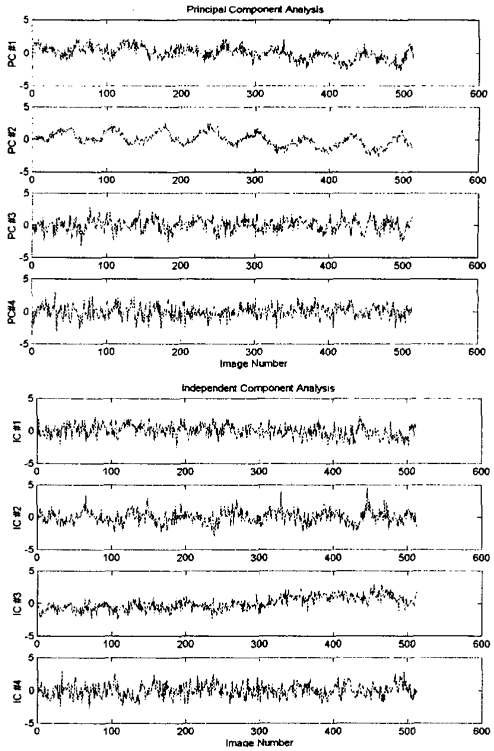

Figure 3: PCA/ICA results before processing.

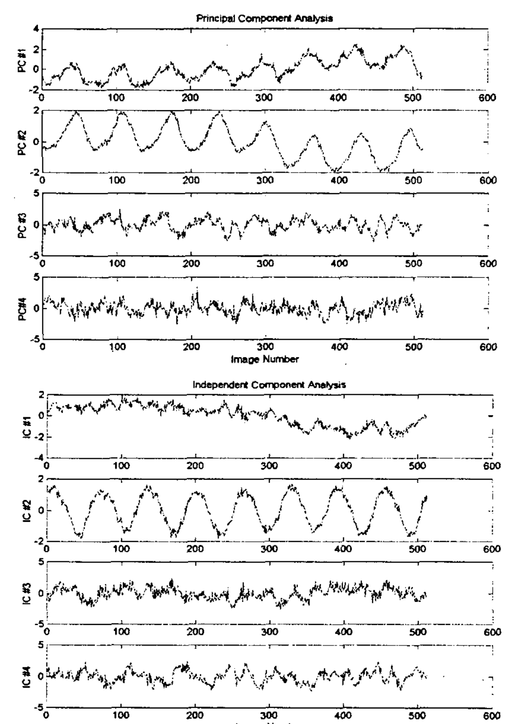

Figure 4: PCA/ICA results after processing.