IDENTIFICATION OF BRAIN ACTIVITY BY FRACTAL SCALING ANALYSIS OF FUNCTIONAL MRI DATA

J.M. Lee[1], J. Hu[1], J.B. Gao[1], K.D. White[2], B. Crosson[3], C.E. Wierenga[3], K. McGregor[2], and K.K. Peck[4]

[1] Electrical and Computer Engineering, [2] Department of Psychology & McKnight Brain Institute
[3] Department of Clinical and Health Psychology, University of Florida, Gainesville, FL 32611, USA
[4] Department of Medical Physics, Memorial Sloan-Kettering Cancer Center, New York, 10021, USA

ABSTRACT

Functional magnetic resonance imaging (fMRI) is a powerful tool for studying brain function, especially related to disease and aging. One of the major tasks of fMRI data analysis is to find a few specific regions involved in certain functionality by studying huge but noisy 3-dimensional spatial plus 1-dimensional temporal data. Therefore, developing simple and reliable signal/image processing algorithms for fMRI data analysis is very important. In this paper, we systematically study how fractal scaling analysis can help us reliably detect brain activity through fMRI data analysis. We examine two types of fractal analysis, the fluctuation analysis (FA) and detrended fluctuation analysis (DFA). We show that while FA is able to readily distinguish active brain regions from in-active ones, it fails to robustly recognize which active regions in the brain are truly involved in certain task. On the other hand, we show that DFA is very effective for this task.

1. INTRODUCTION

In the past decade, functional magnetic resonance imaging (fMRI) has emerged as a powerful non-invasive tool for studying brain function. fMRI works as follows: increasing in brain metabolism by mental processes (e.g., related to neural activities) initiates a cascade of biochemical reactions, resulting in changes of hemodynamic parameters – blood flow and blood oxygenation. The change in hemodynamic parameters in turn alters the measured magnetic resonance signal. This is referred to as blood oxygenation level dependent (BOLD) contrast [1]. fMRI data comprise of time series for about $10^4 \sim 10^5$ small volumns, called voxels, of the brain. The task is then to infer brain activity by analyzing time series in these voxels. This is a huge task, however, since the data are 4-dimensional, of huge size(Gbytes), and noisy. For example, if chance of making a mistake in any one voxel is 1%, then one expects $100 \sim 1000$ errors in every brain map. This may approach the number of truly active voxels in the brain. To appreciate the complexity, we note that some BOLD response signals may not be task-related, but induced by motion or physiological processes in the brain. For simplicity, we shall call the latter by "motion artifacts" in the remain of the paper.

In recent years, tremendous effort has been made to develop novel signal/image processing algorithms for analyzing fMRI data [2–11]. The most popular method used in fMRI data analysis assumes a linear transformation between neural activity and BOLD contrast signals, plus a Gaussian noise residue. Recently, it is found that the residue may not be Gaussian, but a fractal signal [4]. It has been found that BOLD contrast signals without involving any assigned mental task are also fractal-like [12]. Interestingly, by applying fluctuation analysis (FA) and wavelet multiresolution analysis to high temporal resolution fMRI data, it has been shown that the fractal feature of voxel time series can be utilized to separate active and inactive brain regions [5, 6]. However, it is unclear whether fractal analysis can help distinguish motion artifacts from true BOLD responses. In this paper, we quantitatively examine how effective fractal scaling analysis are, including fluctuation analysis (FA) [5] and detrended fluctuation analysis (DFA) [13], in distinguishing among three types of voxels, noise, motion artifacts, and true BOLD responses. We shall show that while FA is able to readily distinguish active brain regions from inactive ones, it fails to robustly recognize which active regions in the brain are truly involved in certain task. On the other hand, we show that DFA is very effective for this task.

The rest of the paper is organized as follows. We briefly describe FA and DFA in Sec. 2. In Sec. 3, we examine the effectiveness of FA and DFA in distinguishing the three types of voxels, true BOLD responses, motion artifacts and noise. Finally, we make a few concluding remarks in Sec. 4.

2. FA AND DFA OF FMRI DATA

Before discussing FA and DFA of the fMRI data, let us briefly describe the data first. The fMRI data were acquired

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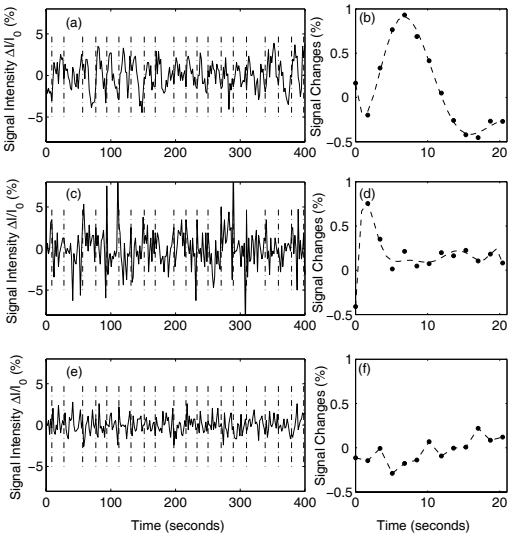

Fig. 1. Representative time series and the corresponding hemodynamic responses of the three types of voxels: (a, b) true BOLD response, (c, d) motion artifact, and (e, f) noise. The dash-dot lines in (a,c,e) indicate the instants when a star flashes. The sampling time is 1.7s.

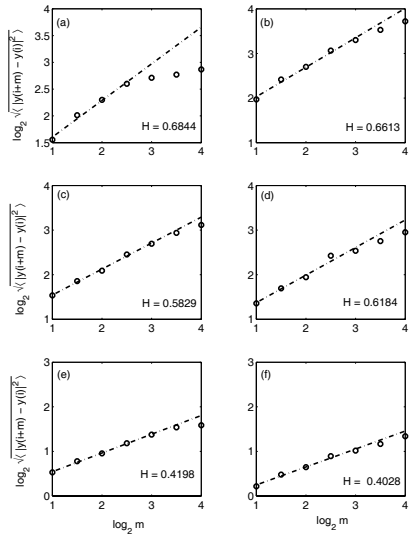

Fig. 2. FA for the three types of voxels. (a, b) true BOLD responses, (c, d) motion artifacts and (e, f) noise.

with a 3T Allegra head-only scanner (Siemens) using a Gradient-Echo Echo Planar Imaging (GE-EPI) (echo time = 30ms; repeat time = 1.7s; flip angle = 70°; resolution = 64×64). The data were collected from motor tasks. The experimental protocol involves a subject pressing a button with the index finger of the right hand three times per event in synchronization with a visually presented flashing star. For each event, the star flashes for 1.7s, followed by variable intervals (i.e., 13.6, 15.3, 17 or 18.7s) with only static scene. The instants when a star flashes are indicated in Fig. 1(a,c,e) by vertical dash-dot lines. Also shown in Fig. 1 are typical time series (Fig. 1(a,c,e)) and hemodynamic response functions (the so-called impulse response functions, IRFs) (Fig. 1(b,d,f)) for the three kinds of voxels, noise (bottom), motion artifacts (middle), and true BOLD responses (top). IRFs were obtained directly from a widely used software AFNI [14]. It is commonly assumed that the voxel time series is generated by the convolution of average neural activity and the IRF. We observe from Fig. 1(a,c,e) that the time series of the noise voxel has the smallest amplitude, while the motion artifact's time series has a few very high peaks.

Now, let us continue to describe FA. Let $x(i), i = 1, \cdots, N$ denote our voxel time series. We form the "*random walk*" process $y(n), n = 1, \cdots, N$ by removing the mean value $\bar{x}$ and forming partial summation, $y(n) = \sum_{i=1}^{n}[(x(i) - \bar{x}]$. We then examine whether the following scaling-law holds or not,

$$F(m) = \left\langle |y(i+m) - y(i)|^2 \right\rangle \sim m^{2H}, \qquad (1)$$

where the average is taken over all possible pairs of $(y(i+m), y(i))$. The parameter H is often called the Hurst parameter [15]. When the scaling law described by Eq. (1) holds, the process under investigation is said to be a fractal process. In fact, when Eq. (1) holds, the autocorrelation for the "*increment*" process, defined as $x(i) = y(i+1) - y(i)$, decays as a power-law, $r(k) \sim k^{2H-2}$, $as \;\; k \to \infty$, while the power spectral density (PSD) for $y(n)$ is $S_y(f) \sim 1/f^{2H+1}$. When $H = 1/2$, the $y(i)$ process is similar to the standard Brownian motion (Bm), and the increment process is similar to the white Gaussian noise (Gn). Generalizations of Bm and Gn are called fractional Brownian motion (fBm) and fractional Gaussian noise (fGn) [15], characterized by $0 \le H \le 1, H \ne 1/2$. When $1/2 < H \le 1$, a fBm is said to have persistent correlations, while when $0 \le H < 1/2$, a fBm is said to have anti-persistent correlations.

In Fig. 2, we show six representative FA curves for each type of the voxels, true BOLD responses (Fig. 2(a, b)), motion artifacts (Fig. 2(c, d)) and noise (Fig. 2(e, f)). We observe that the true BOLD responses have the largest H values, followed by the motion artifacts, and the noise voxels have the smallest values.

Finally, we discuss applying DFA to the fMRI data. We also work with the random-walk-type process $y(n)$. DFA works as follows. First, one divides the time series into $\lfloor N/m \rfloor$ non-overlapping segments (where the notation $\lfloor x \rfloor$ denotes the largest integer that is not greater than x), each containing m points; then one calculates the local trend in each segment to be the ordinate of a linear least-squares fit for the random walk in that segment, and computes the "detrended walk", denoted by $y_m(i)$, as the difference between the original walk $y(i)$ and the local trend; finally, one exam-

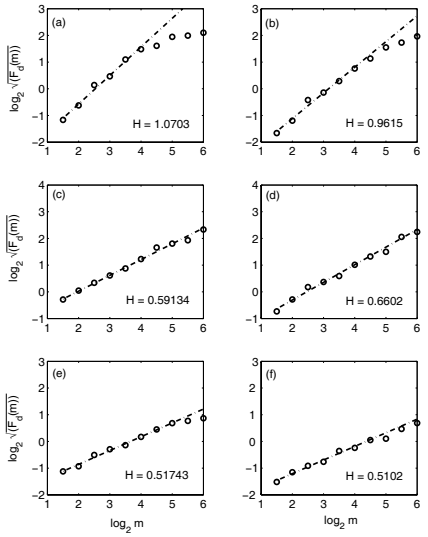

Fig. 3. DFA for the three types of voxels. (a, b) true BOLD responses, (c, d) motion artifacts and (e, f) noise.

ines if the following scaling behavior (i.e., fractal property) holds or not:

$$F_d(m) =< \sum_{i=1}^{m} y_m(i)^2 >\sim m^{2H} \qquad (2)$$

where the angle brackets denote ensemble average of all the segments and $F_d(m)$ is the average variance over all segments. For ideal fractal processes, it has been found that FA and DFA yield equivalent results. In practice, DFA often works more reliably, since it can remove certain trends and nonstationarity.

Fig. 3 shows six representative DFA curves for the three types of the voxels, true BOLD responses (Fig. 3(a, b)), motion artifacts (Fig. 3(c, d)) and noise (Fig. 3(e, f)). We observe that the true BOLD responses have much larger H values than the motion artifacts and the noise voxels. By comparing Figs. 2 and 3, we find that the H values obtained by DFA is always larger than those by FA. This indicates that the data may indeed be nonstationary or have certain trends.

3. EVALUATION OF FRACTAL SCALING ANALYSIS FOR IDENTIFYING BRAIN ACTIVITY

In this section, we examine how effective FA and DFA can be used to distinguish among the three types of voxels, true BOLD responses, motion artifacts and noise. For this purpose, three databases, each containing 400 voxels and consisting of only one type of voxel, were prepared, by focusing only on some regions of interest (ROI), such as primary motor cortex (M1), sensorymotor cortex (SMC), supplementary motor area (SMA), premotor cortex (PM), superior parietal cortex (SPC) and so on. Then we apply FA and DFA to all the time series in these databases. Consistent with Figs. 2 and 3, we observe that the H values for noise are always much smaller than those of true BOLD responses by either FA or DFA, thus it is quite easy to distinguish noise from true BOLD responses by either method. The more challenging task is to distinguish between true BOLD responses and motion artifacts. It is found that for FA, the PDFs of H for the true BOLD responses and the motion artifacts overlap significantly. This indicates that FA is not very effective in recognizing which active regions in the brain are truly involved in certain task. On the other hand, DFA is quite effective for this purpose. Fig. 4 shows the sensitivity and specificity curves of H for the true BOLD response and the motion artifacts and the receiver operating characteristic (ROC) curve by applying DFA in the ROI. A usual choice of H is the one that makes the sensitivity and specificity of H equal, and we obtain the value of 0.7. With this optimal threshold for H, we observe the probability of detection $P_D = 0.87$ and the probability of false alarm $P_{FA} = 0.13$.

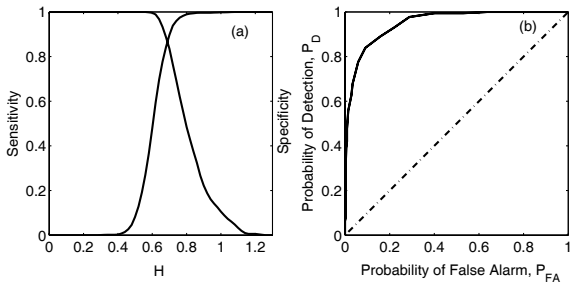

Fig. 4. (a) The sensitivity and specificity curves of H for the true BOLD response and the motion artifacts in the ROI, (b) the ROC curve.

Based on the statistics we obtain from the ROI, we apply DFA on the voxel time series of the whole brain. Fig. 5 shows four representative slices of the brain activation mapping. We observe clear activations in the areas of SMA, PM, M1, SMC and SPC of the brain. These are the areas that are highly expected by neuroscience experts.

Before ending this section, we emphasize that the threshold for H is largely subject independent, and the method developed here applies to fMRI data of different subjects equally well.

4. CONCLUDING REMARKS

In this paper, we have systematically studied how fractal scaling analysis can help us reliably detect brain activity through fMRI data analysis. We have quantitatively examined the effectiveness of FA and DFA in distinguishing

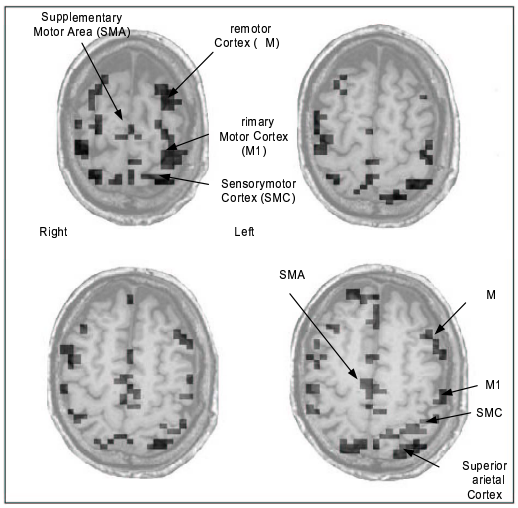

Fig. 5. Brain activation mapping of the fMRI data by DFA.

among the three types of voxels, noise, motion artifacts, and true BOLD responses. It is found that while FA is able to readily distinguish active brain regions from inactive ones, but is not very effective for recognizing which active regions in the brain are truly involved in certain task. On the other hand, by applying DFA on the fMRI data, we obtain a high probability of detection of 0.87 in distinguishing motion artifacts from true BOLD responses. Hence, DFA is very effective for distinguishing true BOLD responses, motion artifacts, and noise. More importantly, the threshold for H is largely subject independent, and the method developed here applies to fMRI data of different subjects equally well. This strongly suggests that the approach proposed here may be developed into an automated method for identifying brain activity.

It is interesting to note that the voxel time series for motion artifacts are more spiky than those for true BOLD responses. The accuracy of the identification of brain activity could be greatly improved by using DFA-based multifractal analysis. We will carefully look into this in the near future.

5. REFERENCES

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