

Adaptive Change Point Detection of Dynamic Functional Connectivity Networks

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Abstract

This study presents a new algorithm to adaptively detect change points of functional connectivity networks in the brain. It uses scans from resting-state functional magnetic resonance imaging (rsfMRI) which is one of the major tools to investigate intrinsic brain functionality. Different regions of the resting brain form networks that change states within a few seconds to minutes. The change points of these networks are different in normal and disordered brain functions and their understanding can help in identification of brain disorders. These changes arise from many unknown factors and extraction of these change points is one of the major challenges in the absence of any ground truth. Our algorithm detects these change points adaptively by computing sum of absolute sign differences of adjacent images in rsfMRI scans using measures from image and video processing. We demonstrate the effectiveness of the proposed algorithm and show that these change points can be detected reliably in both task-based and resting-state networks. The outcomes also point to new directions for future work.

Keywords : Dynamic functional connectivity, Resting-state functional MRI, Adaptive change point detection.

1. Introduction

Studies have reported presence of well-correlated activation in various regions of the resting brain (when a subject is not performing any explicit task and is just thinking) forming networks called ‘functional connectivity (FC)’ networks [1]. Since these networks form in the absence of any task so it is possible to scan patients

with neurological disorders. These FC networks change configurations or ‘states’ within few seconds and the points or times of state changes are called ‘change points’ in this study. These change points in normal and disordered brain functions are different [2] and their identification may differentiate the intrinsic brain functionality of the two groups. However, their identification is a big challenge since there are no ‘ground truths’ for timings of these changes. Even for a normal brain the change points depend on many factors. Despite this lack of the ground truth, studies have used existing methods of capturing the changes in FC networks [3, 4, 5] and a few have developed new methods for this purpose [6, 7, 8]. However, none of these methods focus on extracting just the change points of these FC networks, mostly resulting in extensive computations.

In this study we present a novel algorithm to detect just the change points of dynamic FC networks. After extraction of these change points, any existing method, such as sliding window correlation [3, 4], can be used to capture the relationship of two signals between any two change points. We developed the algorithm by focusing on the findings of some recent studies [7, 9, 10]. [7] reported the presence of Quasi-periodic patterns transitioning from one network to another within a few seconds, observable with naked eyes. Co-activation patterns [9] are spontaneous activities in the brain dominated by brief instances of activations and deactivations. Similar observation was made for spontaneous blood-oxygen-level-dependent (BOLD) events in [10]. The changes from one network to another in all of these studies were detected by the simultaneous sign changes (negative to positive or vice versa) in the intensities of various regions. These findings motivated us to use some image similarity measures to capture these dynamics.

The rest of the paper is arranged as follows. Section 2 provides the algorithm along with its pseudo code. Section 3 presents details of the data used for the study along with the preprocessing steps. Section 4 presents the results of the algorithm’s application on real task-based and resting-state data. Finally we conclude our findings and present some future work in Section 5.

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准周期性的模式

2. Algorithm

Our novel adaptive change point detection algorithm is based on two image similarity measures: statistical sign change (SSC) used in medical image registration [11] and sum of absolute differences (SAD) used in motion detection [12]. In SSC the intensity difference of two images is computed and the change in the signs of the difference is the measure of similarity between the two images. In SAD pixels within a square neighborhood of target image are subtracted from the ones in reference image and then the sum of the absolute difference is computed within the square window.

We hypothesized that in FC networks the change in state is a result of change in signs of image intensities at adjacent time points. So, if we compute the difference between the signs of adjacent normalized images and then compute the sum of their absolute values, we would get largest sums at the point of maximum sign change, reflecting the maximum change in the network state. Hence, extracting a number of largest sums of absolute differences would provide the locations of state changes.

We formed a $N \times M$ matrix, in which N is the number of voxels in a scanned image and M is the number of time points (scans or TRs). This matrix would represent M images with N voxels each and the image vector at any time point t can be represented as $X_t = [x_{1t}, x_{2t}, x_{3t}, \dots, x_{Nt}]'$, $1 \leq t \leq M$. Then we normalized all the images to zero mean and unit variance by using the formula:

$$X'_t = \frac{(X_t - \mu_t)}{S_t}, \quad (1)$$

(μ_t and S_t are sample mean and sample standard deviation of the image at time t). Afterwards, we computed the difference of signs between any two adjacent images.

Similar to the SSC, the change in signs were the indication of the difference (or similarity) for our images. However, in our case difference of signs (instead of intensities) between two adjacent images was the image difference (or similarity). This process was repeated and we obtained a $N \times (M-1)$ matrix, in which columns were the sign differences of the adjacent normalized images. Subsequently, we computed the sum of absolute differences of each column (based on the idea of SAD) at each time point. Finally, we extracted a number of largest sums representing the state change points of the FC networks. Once these change points were extracted, the network transitions could be observed by extraction of images around the change points. Our algorithm is very efficient and computationally inexpensive with

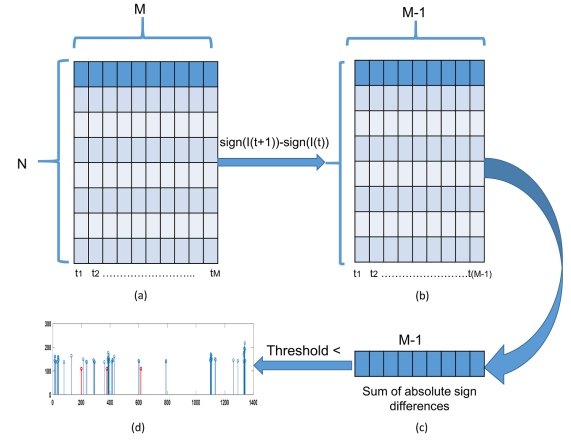


Figure 1. Block diagram of the adaptive change point detection algorithm. (a) Normalized images in columns. (b) Sign difference of adjacent normalized images. (c) Sum of absolute sign differences. (d) Largest sums based above certain threshold.

computational complexity of $O(n)$. Figure 1. shows the block diagram for the sequence of operations in our algorithm.

2.1. Pseudo Code

The pseudo code for the algorithm is given in Algorithm 1. In this code N is number of voxels, M is number of time points, 'Diff' is sign difference, and 'SumOfDiff' is sum of absolute of sign differences. 'sign' represents the sign of intensities of the voxels in an image.

Step 1:

```
for t = 1 to M-1 do
    for n = 1 to N do
        Diff(n, t) = sign(x(n, t+1)) - sign(x(n, t));
    end
end
```

Step 2:

```
for t=1 to M-1 do
    SumOfDiff(:, t) = sum(abs(p(:, t));
end
```

Algorithm 1: Network change point detection

3. Data and Preprocessing

We applied the proposed algorithm on data from a psychomotor vigilance task (PVT) [13] from an earlier study [3]. In this study the subjects were asked to ob-

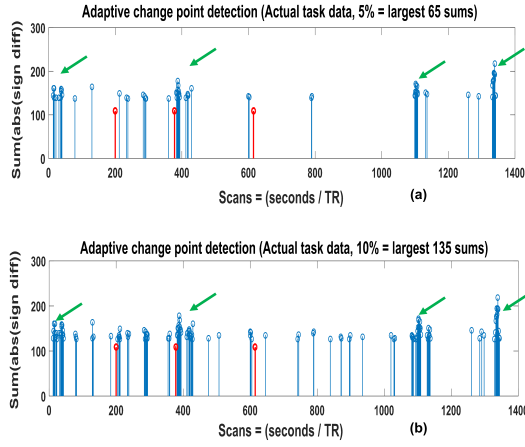


Figure 2. Adaptive change point detection of the vigilance task. The plots are for (a) 5% largest sums and (b) 10% largest sums.

serve the change in the color of a circle from 'black' to 'dark blue' and press a button after detecting this color change. The colors were changed at random time points so the subjects did not have any idea of the task timings prior to its onset. Four fMRI runs of PVT performance were collected from each individual. Two fMRI resting-state runs were collected from each individual. In resting-state runs, individuals were told to lie quietly and look at the black dot that never changed the color (see [3] for details). The sampling rate (repetition time or TR) of the scans was 300 msec and four slices were scanned at every time point. Standard preprocessing steps (slice time correction, motion correction, image segmentation, normalization, and registration) were performed followed by filtering (FIR, 0.01-0.08 Hz).

We applied our algorithm on data from both the task and resting-state scans. The algorithm was applied to the task data since we had information about the state change points (reaction times after the task onset) for these scans providing us with ground truths to compare the results. We chose these specific task scans since the task was very subtle and it was as close to resting state as possible. Hence, we hypothesized that the success of our algorithm on these scans would point towards its probable success for resting-state data also.

4. Results and Analysis

4.1. Real Networks (Task)

We applied the proposed algorithm on task data first. Figure 2. shows the results of algorithm on gray matter from one run of a subject, selected at random.

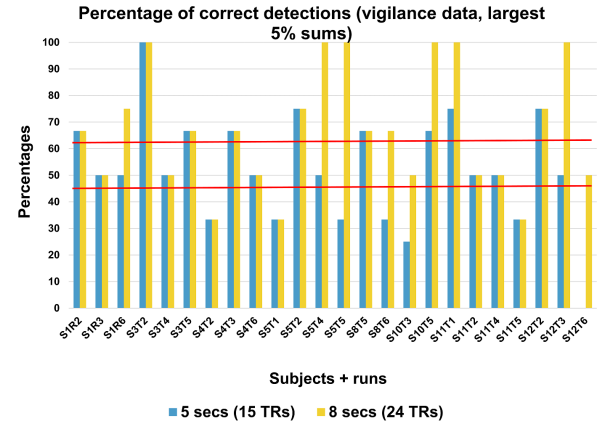


Figure 3. Percentages of correct change point detections in vigilance data (8 subjects, 24 runs).

In both figures the red vertical lines show the reaction time of the task and the blue lines are the largest (a) 5% and (b) 10% sums of absolute differences. Large sums are present around these time points even for the case of 5% largest sums in (a). Moreover, mostly the sums are present in the form of clusters (green arrows) at adjacent time points showing gradual state transition accompanied by large consecutive sign changes. Furthermore, these clusters are present even in the absence of any task onset which may be result of state transition during resting-state of just false alarms.

Figure 3. shows the percentage of times the largest 5% sums were within 5 seconds or 8 seconds of the reaction time for eight subjects and twenty four runs. Red horizontal lines show the mean percentages. As expected the mean percentage is higher for detection within 8 seconds of the reaction time. It should be noted here that these plots are only from 5% (65 time points) of the largest sums. Increasing this sum is expected to improve the percentage detection.

4.2. Real Networks (Rest)

As seen from Figure 2., clusters of largest sums of absolute differences were obtained even in the absence of any task which may be due network transitions in the resting-state. Based on this observation we applied the algorithm on resting-state data from the same study and results for one randomly selected subject is given in Figure 4. We plotted all four slices at the start and at the end of a cluster of large sums from (a) in (b) and (c). The start and end of the cluster are pointed to by red lines (a). It can be observed that there is a significant amount of transition in the network between these two

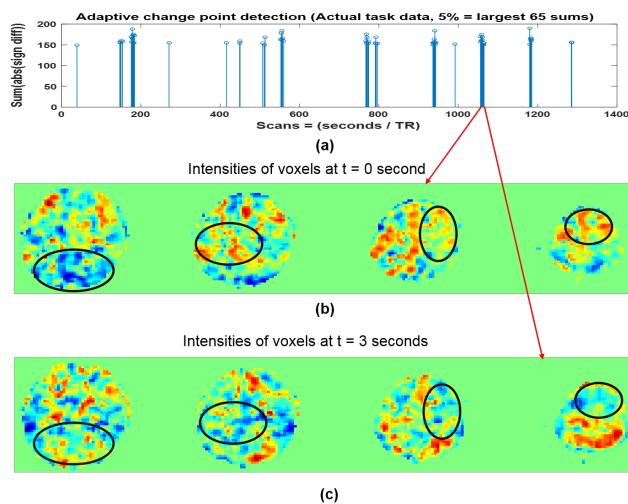


Figure 4. Adaptive change point detection of resting-state network from a randomly chosen subject and run.

time points (shown by black ovals) that are only three seconds (9 scans) apart.

5. Conclusion and Future Work

This study presents a new algorithm for adaptive change point detection of dynamic FC networks. Using task-based and resting-state scans we showed that this algorithm may detect the randomly distributed network change points quite reliably. Our algorithm is simple and efficient, however, it has a few limitations. Intensity changes occur in FC networks at all times resulting in sign differences between any two adjacent images. Our algorithm is based on the hypothesis that the largest sums would indicate the presence of state changes. However, in the absence of any information about the underlying network transitions, there is no way of knowing how many of these largest sums to analyze. Furthermore, these change points were also detected in the absence of any task which may be due to network changes in the resting-state or just false alarms. Additionally, the algorithm is applied on all gray matter providing no information about the changes in regions of any specific network, around the change points. Future studies can modify the algorithm to set a threshold on the number of largest sums, perform some significance test for probable false alarms, and may identify if the change points are present in the expected brain regions for task-based fMRI.

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