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Synchronized brain activity changes related to perceptual alternations

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Abstract: When we look at ambiguous figures, perception spontaneously changes from one to the other (perceptual alternation). We measured the brain activity from subjects who observed the Necker cube, one of the most famous ambiguous figures, using magnetoencephalography (MEG). To identify the brain activity inducing perceptual alternation, we propose a novel change-point detection method using spectral clustering to recurrence plots, and apply to measured data. Synchronized activity changes were detected at parietal channels.

Keywords:Perceptual Alternation, Magnetoencephalography, Recurrence Plot, Spectral Clustering

I Introduction

Ambiguous figures are figures which allow multiple perceptions. When we look at ambiguous figures, perception spontaneously changes from one to the other. This phenomena is called "perceptual alternation". Because consciousness alternates without any stimulus changes, perceptual alternations are thought to be related to perceptual consciousness.

When perceptual alternations occur, brain activity should change in some way. To detect changes of brain activity, we propose a novel change-point detection method that divides "recurrence plots", which visualize time series, by a graph partitioning method "spectral clustering" and apply it to signals measured by magnetoencephalography (MEG). Synchronized changes are detected by the proposed method in the parietal area.

II Experiment

Subjects observed the Necker cube (fig. 1) which is the famous ambiguous figure for 60sec, and pressed a button by the right hand when perception changed. We measured the brain activity using MEG with 160 channels. The sampling rate is 1000Hz.

Some MEG signals measured from parietal channels are shown in fig. 2. Our purpose is to detect changes of brain activities related to perceptual alternations from these signals.

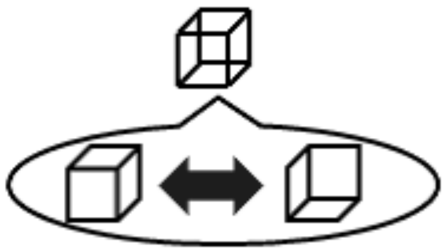


Figure 1: Necker cube (top) and its two perceptions (bottom).

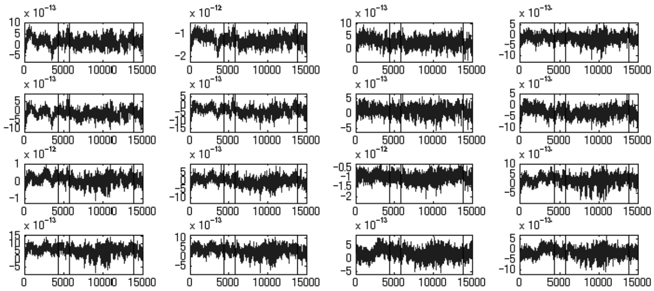
III Method

1 Reconstruction of the state space

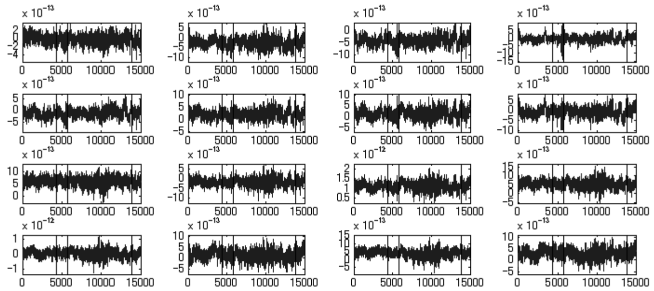
Generally, we cannot observe all of variables of dynamical systems. Therefore, it is necessary to reconstruct the state space of the system from observed time series. It is known that the delay coordinate,

$$\mathbf{x}(t) = (s(t), s(t+\tau), \dots, s(t+(m-1)\tau)),$$

becomes an embedding of the attractor of the dynamical system with the dimension d when $m > 2d$[1]. Here τ is the delay and m is the embedding dimension.

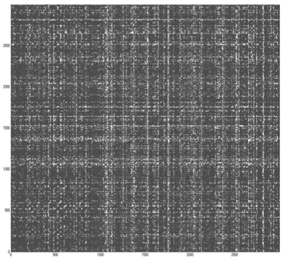


(a) Left parietal channels.

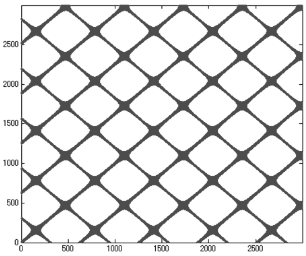


(b) Right parietal channels.

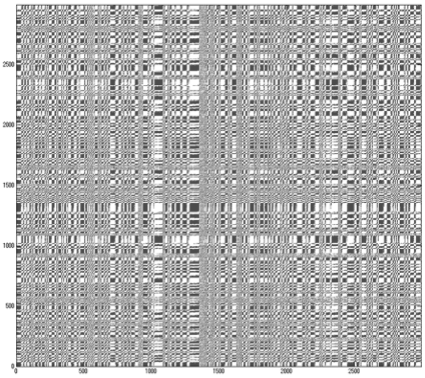
Figure 2: Measured signals from left parietal channels (a) and right parietal channels (b). The time when a subject pressed a button is indicated by black vertical lines. Horizontal axes represent time(ms).



(a) White noise.



(b) Sine wave.



(c) Lorenz equation.

Figure 3: Examples of recurrence plots.

2 Recurrence plots

Recurrence plots[2] visualize time series as two dimensional plots whose horizontal and vertical axes correspond to time. The recurrence plot of a time series $\{s(t)\}$ is defined by using the delay coordinates as follows:

$$\mathbf{R}(r)_{i,j} = \begin{cases} 1, & (\|\mathbf{x}(i) - \mathbf{x}(j)\| \leq r), \\ 0, & (\|\mathbf{x}(i) - \mathbf{x}(j)\| > r), \end{cases} \tag{1}$$

where r is the threshold. Recurrence plots visualize various features of time series. Examples of recurrence plots are shown in fig. 3. Fig. 3(a) is the recurrence plot of white noise. In recurrence plots of stochastic data, points are distributed randomly. Recurrence plots of periodic data like a sine wave have lines parallel to the diagonal line (fig. 3(b)). Recurrence plots of chaotic data are complex but not random. Fig. 3(c) is the recurrence plot of the Lorenz equation.

3 Spectral clustering

Spectral clustering partitions a graph to disjoint sets that minimize a certain cost function. We used "normalized cut"[3] as the cost function. When we partition a graph $(\mathbf{V}, \mathbf{E})$ to subgraphs $(\mathbf{A}, \mathbf{E_a})$ and $(\mathbf{B}, \mathbf{E_b})$, a normalized cut is defined as follows:

$$\begin{aligned} NCut(\mathbf{A}, \mathbf{B}) &= \frac{\sum_{u \in \mathbf{A}, v \in \mathbf{B}} \mathbf{W}(u, v)}{\sum_{u \in \mathbf{A}, t \in \mathbf{V}} \mathbf{W}(u, t)} \\ &\quad + \frac{\sum_{u \in \mathbf{A}, v \in \mathbf{B}} \mathbf{W}(u, v)}{\sum_{u \in \mathbf{B}, t \in \mathbf{V}} \mathbf{W}(u, t)}, \end{aligned} \tag{2}$$

where $\mathbf{W}$ is the adjacency matrix whose element $\mathbf{W}(u, v)$ is the weight of the edge between the vertex u and v. Minimizing the normalized cut is equivalent to minimizing the Rayligh quotient:

$$\frac{\mathbf{y^T}(\mathbf{D} - \mathbf{W})\mathbf{y}}{\mathbf{y^T D y}},$$
$$\mathbf{y}_i = \begin{cases} 1, & (v_i \in \mathbf{A}), \\ 0, & (v_i \in \mathbf{B}). \end{cases}$$

If $\mathbf{y}$ is relaxed to one that takes real values, we can minimize the normalized cut by solving the eigenvalue system:

$$\mathbf{D}^{-\frac{1}{2}}(\mathbf{D} - \mathbf{W})\mathbf{D}^{-\frac{1}{2}}\mathbf{z} = \lambda \mathbf{z}, \tag{3}$$

where $\mathbf{D}$ is the diagonal matrix whose diagonal elements are degrees of vertices and $\mathbf{z} = \mathbf{D}^{1/2}\mathbf{y}$. Because the matrix $\mathbf{D}^{-1/2}(\mathbf{D} - \mathbf{W})\mathbf{D}^{-1/2}$ is the symmetric positive semidefinite matrix, the minimum eigenvalue is 0 and the corresponding eigenvector is the vector whose all elemtents are the same value. This corresponds to the trivial partition $\mathbf{A} = \mathbf{V}, \mathbf{B} = \phi$ or $\mathbf{A} = \phi, \mathbf{B} = \mathbf{V}$. Hence, when $\mathbf{z}_1$ is the eigenvector corresponding to the second smallest eigenvalue, $\mathbf{y} = \mathbf{D}^{-1/2}\mathbf{z}_1$ is the partition minimizing the normalized cut. If $\mathbf{y}_i > 0$, $v_i \in \mathbf{A}$, otherwise $v_i \in \mathbf{B}$.

4 Proposed method

We regard recurrence plots $\mathbf{R}$ as adjacency matrices $\mathbf{W}$, and apply spectral clustering. If t and $t+1$ are included in different subgraphs, we detect the time t as the change-point. Because the order of rows and columns of the adjacency matrix is meaningless, permutation of those have no effect to the result of spectral clustering. However, rows and columns in the recurrence plot are in the temporal order, and hence rows and columns cannot be permutated. Therefore, application of spectral clustering to recurrence plots discards the temporal information. To avoid this problem, we generate a new matrix by adding edges between vertices i and j when time i and j are sufficiently close.

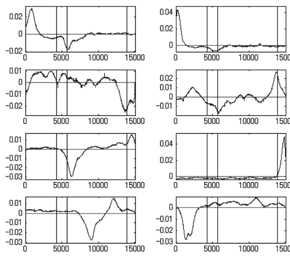
$$\hat{\mathbf{R}}_{i,j} = \begin{cases} 1, & |i-j| \le n, \\ \mathbf{R}_{i,j}, & |i-j| > n. \end{cases} \quad (4)$$

We apply spectral clustering to this matrix. This matrix was used in the study of reconstructing time series from recurrence plots[4].

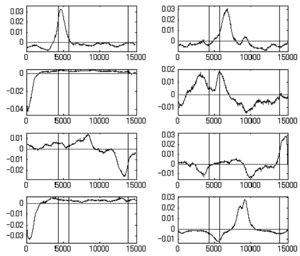
IV Result

We analyzed signals measured from 64 channels located at left parietal, right parietal, left occipital, and right occipital areas. To avoid artifacts, we extracted 8 components from 16 signals measured from each area by blind source separation using ICALAB toolbox[5][6]. We applied the proposed method to the extracted components. We used embedding dimension $m = 25$, delay $\tau = 1$, and $n = 70$. Thresholds of recurrence plots were determined to fix recurrence rate (probability that we find a point in a recurrence plot) to be 0.0015. Eigenvectors obtained by the spectral clustering to matrices $\hat{\mathbf{R}}$ are shown in fig. 4.

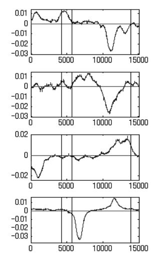
For example, positive (negative) components in the eigenvectors can be interpreted as corresponding to one perception, and absolute values of the components can be interpreted as strengths of perception (fig. 5). Then, eigenvectors are considered as a sequence of perceptual states.



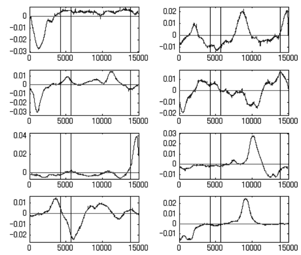
(a) Left parietal area



(b) Right parietal ares



(c) Left occipital area



(d) Right occipital area

Figure 4: Eigenvectors obtained by spectral clustering. The time when a subject pressed a button is indicated by black vertical lines. Horizontal axes represent time(ms).

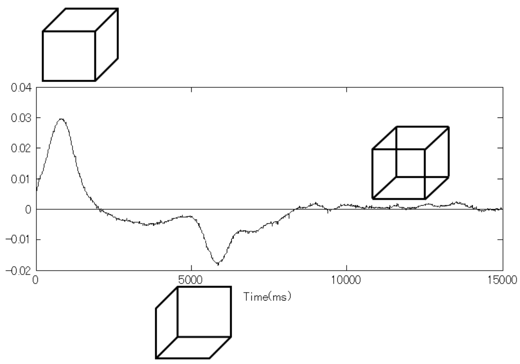


Figure 5: The eigenvector and percptual state.

To investigate synchronaization of changes of brain activities when perceptual alternations occur, we calculated cross-correlation functions of these eigenvectors. The peaks of absolute value represents degree of synchronization and the delay of peaks represents the delay of changes of brain activity. Peaks of absolute value and delay are shwon in fig. 6. In the left and right parietal areas, changes of many components are highly correlated (fig. 6(a)). These results imply that changes of brain activities in these area are synchronized. Moreover, right parietal changes procede left parietal changes(fig. 6(b)).

V Conclusion

We proposed the novel change-point detection method in which spectral clustering is applied to recurrence plots. We applied the proposed method to signals measured by MEG from subjects observing the Necker cube. Changes of brain activities related to perceptual alternations are detected by the proposed method. Cross-correlation functions of eigenvectors obtained by the proposed method indicate that brain activities were highly correlated in parietal area, and the right parietal activity precedes the left parietal acitivity. These results imply that changes of brain activities in the parietal area are related to perceptual alternations and the right parietal activities change earlier than the left parietal acitivities when perceptual alternations occur.

Acknowledgements

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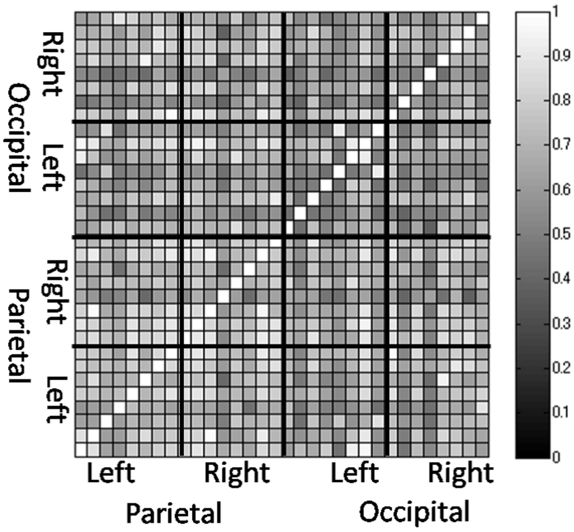
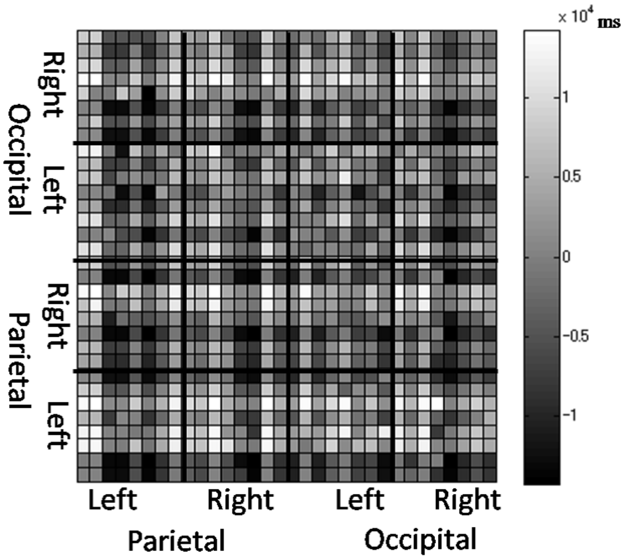


(a) Peaks of absolute values of cross-correlation functions



(b) Delay of cross-correlation functions

Figure 6: Peaks of absolute values and delay of cross-correlated functions calculated from eigenvectors obtained by spectral clustering.