Journal of Electronic Research and Application, 2022, Volume 6, Issue 1
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Cognitive Analysis of Auditory Temporal Sequence Information Difference Based on Network Switching

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Abstract: Auditory sense is an important way for people to receive and interact with foreign information. In different environment, the auditory sense changes. Therefore, it is necessary to find a detection method that can detect hearing in a timely manner. In this paper, EEG experiments were used to construct and compare brain functional networks in different states, and auditory state models were constructed with different auditory input signals. Secondly, the cross-correlation method is used to slice the signal and construct the adjacency matrix. Louvain community detection algorithm is used to process the data and calculate the network conversion rate under different parameters. It is concluded that the network conversion rate can be used to analyze the temporal variation of auditory information under the condition of controlled parameters. This indicates that the network conversion rate can also be used as a method to analyze auditory signals in the future.

Keywords: Brain functional networks, EEG, Network switching, Auditory signals

Online publication: February 18, 2022

1. Introduction

The human brain is an extremely complex system. For any task, multiple functional brain regions need to coordinate and work together to achieve it. At the end of the 19th century, the scientists of the day theorized that each brain region (composed of neurons) has only a specific function. On this basis, the brain is regarded as a network, the structural or functional regions of the brain are taken as nodes, and the correlation characteristics between nodes are taken as edges to analyze the behavioral performance of the human brain through the features of this brain network. People divide the brain into multiple regions according to their functions. However, human behaviors and conscious behaviors are not determined by a single region but rather, realized by the cooperation of multiple regions of the whole brain. The brain also realizes information interaction through the interconnection between various regions and clusters of work. Therefore, the analysis of the human brain network can provide a new method for research work to better understand the multi-region cluster working mode of the brain from a global perspective. In some clinical trials on neurological diseases, the brain network analysis method showed good performance in the diagnosis and treatment of diseases. Progress has been made in the early detection and diagnosis of epilepsy, schizophrenia, depression, and Alzheimer's disease. Through the analysis of the brain network map, the abnormal state of neurological diseases in the brain network is explored, and abnormal network topological indicators in the disease state are sought for diagnosis and intervention.

In 1978, Naatanen and other researchers proposed and confirmed that an auditory evoked potential component induced by a "deviation" stimulus randomly appearing in a repeated "standard" stimulus sequence is a differential wave between two stimulus responses induced by auditory changes of 100 ~ 250 ms, which is known as a mismatched negative wave (MMN) [1]. MMN can objectively reflect the brain's automatic processing of sensory information, especially auditory information. As an electrophysiological indicator of the brain's sensory information processing, MMN has great application potential in cognitive neuroscience and clinical diagnosis. At present, it is difficult for most of the auditory information detection to detect in a timely and effective manner, so a real-time detection method is needed. Since auditory feedback will appear in the brain, it is possible to conduct differential research on auditory temporal information by collecting changes in the brain information characteristics.

Multilayer network analysis is a new graph theory model. In this model, network nodes are connected in time and space [2]. Previous studies on cognitive tasks have shown that multilayer modularization and network switching have inherent neurobiological basis in multilayer network analysis, but the dynamic relationship between network switching and functional connection time series, as well as the relationship between network switching time series and network connections and complexity remain unknown.

The audio clips used in this paper are comprised of 333 Hz sinusoidal waves modulated by different signal amplitudes. The frequency of the periodic signal is used to imitate different music speeds. The frequency range of the modulated signal is from 2.3 Hz to 2.9 Hz, and the music speed range covers from 123 BPM to 164 BPM. There are altogether 14 types of audio clips. The beat consists of an envelope of asynchronous Hanning window functions in the modulating signal. After the audio clips were made, two were selected as audio stimuli for an experiment. There are two types of audio stimuli, one that has constant music speed and the other with varying music speed. A total of 21 audio stimuli were used twice per clip.

In this paper, based on the collected audio clips, EEGLAB was used for independent component analysis to separate the blind source signals and complete the pre-processing of the collected data. Then the brain networks in both states were studied. The two kinds of data were analyzed from the time domain. Based on existing studies, the important parameter module degree in Louvain algorithm was taken as the characteristic parameter of the brain network to explore the objective test index for effectively judging different audio signals.

2. Methods

2.1. ICA data preprocessing

Independent component analysis (ICA) was performed on the collected data using EEG to remove the artifact. The purpose of ICA is to find out the independent parts that constitute the signal and correspond to the analysis of higher-order statistics. Based on the "virtual channel" of spatial transformation, it analyzes the linear changes of data in a single-channel scalp [3]. In EEGLAB, ICA is mainly used to separate blind source signals. Blind source separation is the separation of the source signal from the noise when the source signal and the noise are mixed or unknown. The ICA algorithm is as shown in **Table 1**.

Table 1. ICA algorithm

Input: Observational data X
Output: Independent component Y
1: Centralize the observed data X
2: Whiten the observed data X
3: Initial unmixable matrix W
4: While W does not converge to do
5: $Y \Leftarrow WX$
6: $\Delta W \Leftarrow \eta(I - \Psi(Y)Y^T)W$
7: $W \Leftarrow W + \Delta W$
8: end while
9: $Y \Leftarrow WX$
10: return Y;

2.2. Pearson correlation coefficient matrix

Cross-correlation can measure the linear correlation between any two different time values of signals. From the perspective of time domain, this paper chose the cross-correlation method, namely sliding time window analysis based on Pearson correlation coefficient. The time window size is set as T, and s as the time point. The Pearson correlation coefficient of electrode X and Y is as follows:

$$r_{XY,s} = \frac{\sum_{t=1}^{T}(X_s[t] - \overline{X_s})(Y_s[t] - \overline{Y_s})}{\sqrt{\sum_{t=1}^{T}(X_s[t] - \overline{X_s})^2}\sqrt{\sum_{t=1}^{T}(Y_s[t] - \overline{Y_s})^2}} \quad (1)$$

$Xs[t]$ represents the EEG signal of the t node in the time window of electrode X at time node s. $\overline{x}_s$ represents the mean of all EEG signals in the time window of electrode X at time node s. For each time point, an adjacency matrix with weighted undirected network can be obtained. If the total number of time nodes is set as N, a multi-layer adjacency matrix with weighted undirected network $W = (W_1, W_2, \ldots, W_n)$ can be obtained.

2.3. Louvain community detection algorithm

Louvain community detection algorithm is a graph algorithm model based on turn-by-turn heuristic iteration optimization of module degree, which detects the best community by maximizing the module degree Q of each layer [4]. This algorithm can quickly and effectively divide large networks into communities and has high precision. It can identify hierarchical community structures more effectively. Louvain algorithm is divided into two steps (**Figure 1**).

Step 1 is the maximum modularity division. Through each node as a community, calculate the node at the same time from the node to join other communities after the change of the degree of module Q, and record the biggest ΔQ; if $max\Delta Q > 0$, the biggest distributing the node ΔQ the neighbor nodes in the community, otherwise remain unchanged. This is repeated until the community to which all nodes belong to is no longer changing.

The second step is community consolidation. All nodes in the same community are compressed into a new node. The weight of edges between nodes in the community is converted into the weight of rings of new nodes, and the weight of edges between communities is converted into the weight of edges between new nodes. Step 1 is then repeated until the entire module degree does not change.

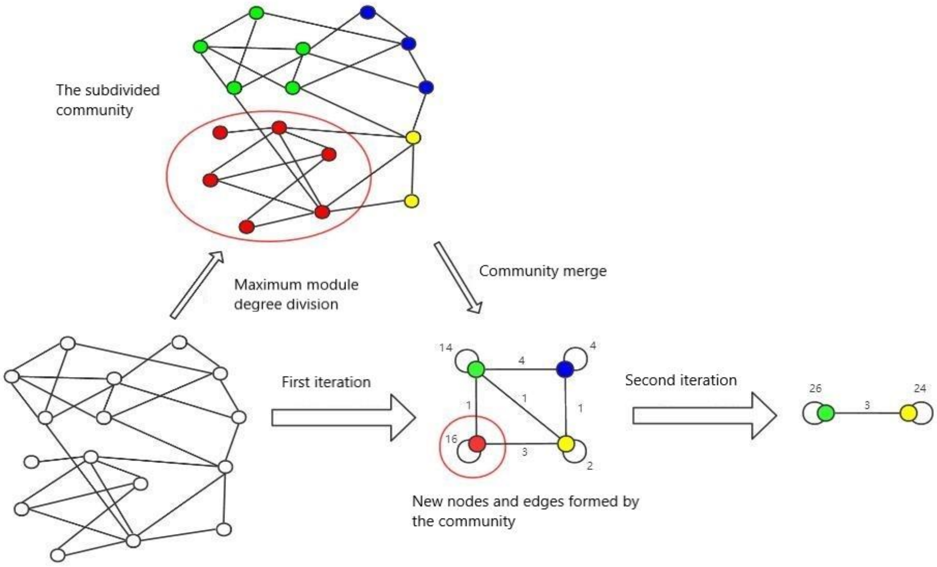


Figure 1. Schematic diagram of Louvain community detection algorithm

2.4. Network conversion rate

The conversion rate of brain networks is defined as the maximum degree of modularity when the community detection algorithm converges after many iterations. Modularity, whose physical meaning is the difference between the number of edges of nodes in the community and the number of edges in random cases, is a commonly used method to measure the strength of network community structure. As proposed by Mark Newman, it is defined as follows:

$$Q = \frac{1}{2m} * \sum_{ij} \left[A_i j - \frac{k_i * k_j}{2m} \right] \delta(C_i, C_j) \tag{2}$$

A good community is closely connected internally, but sparsely connected externally. The larger the module degree, the better the corresponding community division. The value range of modularity is set between 0 and 1, controlled by the parameters γ and ω. Among them γ refers to the network topology strength, while ω refers to the multilayer network connection strength between each layer [3]. The calculation formula of multilayer module degree Q is as follows:

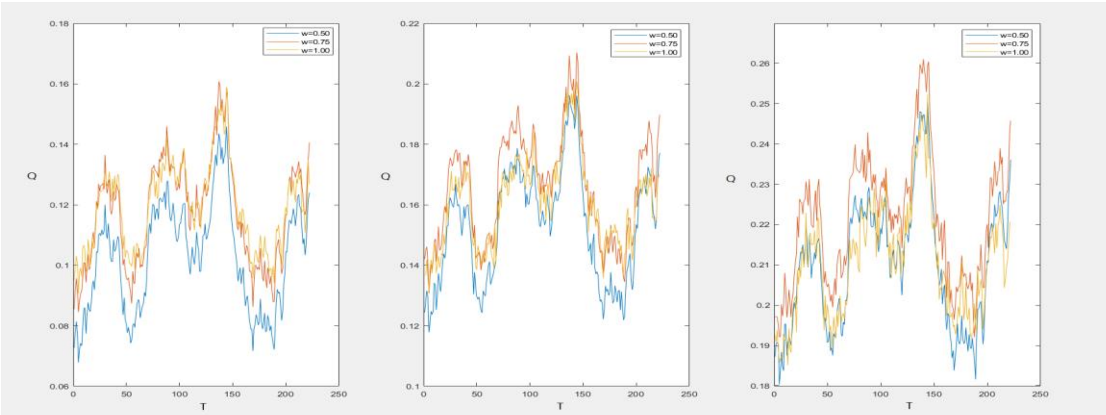
$$Q(\gamma, \omega) = \frac{1}{2\mu} \sum_{ijsr} [(A_{ijs} - \gamma_s \frac{k_{is} k_{js}}{2m_s}) \delta(M_{is}, M_{js}) + \delta(i, j) \omega_{jrs}] \, \delta(M_{is}, M_{js}) \tag{3}$$

In formula (3), A_{ijs} represents the edge weight between node i and node j in the brain network at time node S. k_{is} represents the weights and of all edges connected to node i in the brain network at time node S. m_s represents the k value and of all nodes in the brain network at time node S; M_{is} represents the community to which node i belongs in the brain network at time node s; $\delta(M_i, M_j)$ and $\delta(i, j)$ are used to determine whether M_i and M_j, as well as i and j belong to the same community, if 1, or 0. As the multilayer network used in this experiment belongs to the time series network, the values of all time nodes and network nodes y and w are the same.

Take a time window and set its size as I. At time point S, for multilayer network A, there is its multilayer network $SubAs = (A_s, A_{s+1}, \ldots, A_{s+I-1})$ in the time window, and substitute $SubAs$ into A in the above formula to obtain the module degree Q_s of the sub-network, namely the conversion rate Q_s of multilayer network A at time point S. Sliding the time window, the time-based conversion rate vector $Q = (Q_1, Q_2, \ldots, Q_n)$ of the multi-layer network *A* can be obtained.

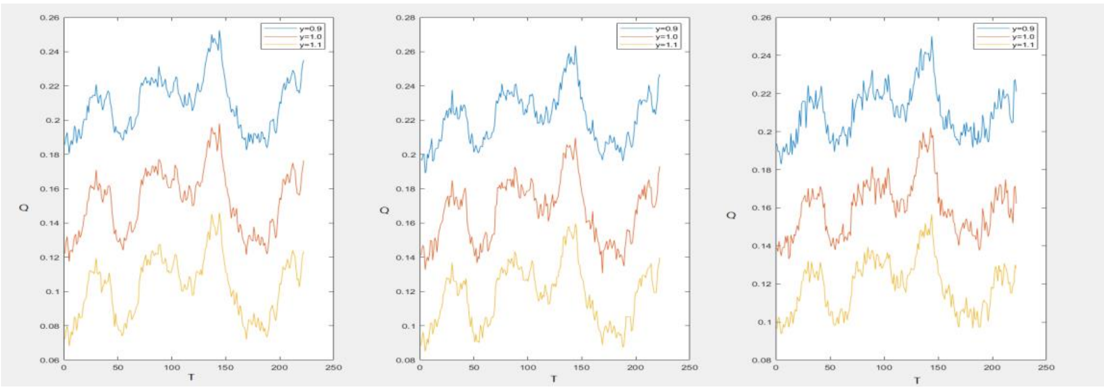
3. Results and analysis

Based on the results of Pedersen and other researchers [5], the data time length selected in this experiment was 1000 ms, with a total of 250 nodes at a sampling rate of 250 Hz. After pre-processing, the data were averaged by stacking, and then calculated by using the cross-correlation method based on Pearson correlation coefficient. The sliding time window was set as 5 (20 ms) to generate the correlation coefficient matrix. The value in the matrix was an absolute value, and thresholding operation was carried out by using ozu threshold. The network window size was set to 25 (100 ms), and according to the combination of different control parameters *y* and *w*, network conversion rate *Q* of all normal music speed audio and music speed varying audio was calculated according to the method described above. Among them, $\gamma \in \{0.9,1,1.1\}$, $\omega \in \{0.5,0.75,1\}$.



(a) *y* = 1.1 (b) *y* = 1 (c) *y* = 0.9

Figure 2. Same *y*, different *w* at the same time, conversion rate curve contrast



(a) *w* = 0.9 (b) *w* = 1 (c) *w* = 1.1

Figure 3. Same *w*, different *y* at the same time, conversion rate curve contrast

Figure 2 and **Figure 3** will be the conversion rate vector in time order to curve out, from which it can be seen that the main effect of the parameters *y* and *w* on the conversion rate is the value taken, in the same multilayer network, the conversion rate and *y* value as a whole is negatively correlated, while *w* value as a whole is positively correlated. The overall trend of the conversion rate curve is less influenced by *y* and *w*.

4. Conclusion

Cognitive computing research provides an important reference for the construction of brain-like artificial intelligence technologies and methods. Using cognitive computing methods to improve existing artificial intelligence technologies and differentiated analysis from auditory cognition can broaden the direction of emotion recognition. With auditory attention and psychological mood as the main research subjects, through the Pearson correlation-based brain network, using the Louvain algorithm, the proposed network conversion rate as a new feature for emotion recognition, and the proof that this method exhibits better universality, the emphasis can be on people's psychological mood for effective identification. In addition, other features such as node degree, clustering coefficient, and centrality are combined to classify, which can better identify the difference in the impact of music with different rhythms on people's emotions.

Disclosure statement

The authors declare no conflict of interest.

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