Complex networks derived from time series and its application in EEG-based emotion assessment with convolutional neural networks

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Abstract. Construction the complex network paradigm, it is evidenced a new tool for exploring the dynamic mechanism hiding in the time series data which is a trajectory of complex system. This method has been applied in various domains gradually, such as physics, engineering, medicine and economics. In this paper, a new method for network paradigm transforming based on separating with the isoprobability is proposed, then it is applied in EEG signal analysis. The measures of transformed networks from 62-electrods ESI NeuroScan platform were used to construct EEG map. A three-layer convolutional neural network with 15 input channels were built so as to implement EEG-based emotion assessment. By nine fold cross validation, the structure of the convolutional neural network is improved. The simulation shows that our approach is better than differential entropy features based method.

1. Introduction

The purpose of time series analysis is to revealing the evolution law of the original complex system by some appropriate data analysis methods. The complex network paradigm of time series is a novel method, which achieves significant results in mining global features of non-linear systems. It is widely used in dynamic system, financial time series, medical electrical signals and other fields.

Generally speaking, researches related to complex networks can be concluded to four aspects: 1. How does various complex networks generate? This issue focuses on the generation dynamical process and mechanism, especially for some special structures of the network, one can acquire more in [1]; 2. Taking the complex network as the information flowing channel, the propagation dynamics over complex networks has attracted great concerns. The key point is the relationship between network structure characteristics and information transmission performance[2][3]; 3. Complex systems are modeled to complex networks, by which the evolutional mechanism of the complex systems are analyzed through its structure. For example, Gao create a new theoretical framework to analyze complex factors fault-tolerant systems [4], others work can be seen in [5][6][7]; 4. The structure of complex networks is used to improve the efficiency of existing tools, such as the reservoir computation [8].

Mapping time series to network and its application is what we concerned in this paper. Through the complex network paradigm of time series, researchers could figure out the dynamic evolutionary mechanism of the original complex system in a certain degree. It is a new approach to analyze time series in the past few years. For instance, by mapping the fractional Brownian motion series into a
scale-free visibility graph (VG), its Hurst exponent is estimated [9]. Supriya extended a weighted VG to detect epilepsy via network measurements [10]. Gao combines the adaptive optimal kernel time-frequency representation with VG to recognize epileptic seizures from EEG signals [11]. Using 30-channel steady-state visual evoked potential (VEP) signals, a kind of brain network, which is related to fatigue behavioral, based on the adaptive optimal kernel time-frequency representation is proposed [12]. Similar to nonlinear series, Zhang proposed a surrogate generation method for scale-free complex networks [13]. To explore oil-water two-phase flow system, a multiplex network-based sensor information fusion model is developed, and under appropriate weighted network measures, different spatial local epidemic behaviors can be distinguished [14]. Moreover, this paper showed an instance on its application, that is, EEG-based emotion assessment. Take human-computer interaction for example, user experiences could be enhanced greatly, if a computer understands user emotion as a kind of feedback [15]. Some mental health researches confirm that emotions have a certain impact on people's physical health, thus emotional recognition is helpful to develop intelligent mental health monitoring technology [16]. Since the brain activity process cannot be disguised, the emotion recognition method based on EEG or brain imaging technology has become a very hot issue in the field of cognitive science. For example, by the common spatial pattern algorithm, Li extracted some features from filtered EEG data and the classification is carried out by SVM [17]. In [18], Zheng extracted the asymmetry of the front and rear, left and right symmetrical electrodes for EEG-based emotional recognition, and explored the best leads and frequency bands. In [19], autoencoder (AE) -based unsupervised feature learning is used to emotion recognition. In [20], Moon uses a convolutional neural network approach based on power spectral density (PSD) of EEG signals to realize emotion assessment. As we all know, convolutional neural network develops so rapidly that many successful examples are gained, especially in pattern recognition. Take EEG map constructed by the characteristics of EEG signals as an entry point, we mapped EEG signals to a group of complex networks. Then, the establishment of EEG map is based on the network characteristics. In the end, we constructed an emotion classifier based on a convolutional neural network.

The rest of paper is organized as follows: in Section 2 we expounded our method in details, then a specific simulation was implemented in Section 3, finally we draw a conclusion and made a further discussion.

2. Methodology

In this section, we propose the approach of mapping a time series to a complex network, then briefly introduce some measurements which used to build EEG map. At last, we construct a convolutional neural network to classify the emotional feature based on EEG signals. The whole process is shown in a flow diagram, see Figure 1.

![Figure 1. Flow chart.](image)

2.1. Mapping time series to complex networks

A single dimensional time series is regarded as a sequence of different status which are symbolizations of fragments, if it was divided by an appropriate method. In our approach, the complexity of a time series is used as the reference standard for division. Then, the symbolic process is completed based on the distributions of digital features of fragments. After that, the complex network is constructed by probability transition method.
2.1.1. Multi-scale entropy (MSE). By the probability of new patterns emergence under different scales, MSE quantifies the complexity of a sequence. Here is a short description about it. Let \( \{ r_t \mid r_t = x_{t+1} - x_t \} \), which has less autocorrelation than \( \{ x_t \} \), where \( \{ x_t \} \) is the observation time series. Let \( \{ R_t \} \) be the m-dimension embedding vectors sequence. \( \sigma_{\{r_t\}} \) on behalf of the standard variance of \( \{ r_t \} \) can be used to judge whether there is a new pattern. For a scalar \( \theta \), let

\[
C_m^m(\theta) = \frac{n_j}{N - m}
\]

(1)

where \( m \) is the embedding dimension, \( n_j \) is the number of vectors of \( \{ R_t \} \) which lies in the neighborhood of \( R_t, U(R_t, \theta \cdot \sigma_{\{r_t\}}) \). Note that the distance is derived from the infinity norm, and \( N \) is the length of \( \{ r_t \} \). Note that for a finite dimension vector \( \bar{a} = (a_1, \cdots, a_s) \), its infinity norm is defined as the infinity norm for \( 1'(a_1, a_2, \cdots, a_s, 0, 0, \cdots) \).

The sample entropy (SE) of \( \{ r_t \} \) with scale \( \tau \) is defined as:

\[
SE_{\tau} = \lim_{N \to \infty} \ln \left( \frac{\Phi^{m+1}}{\Phi^m} \right)
\]

(2)

where

\[
\Phi^m = \frac{1}{N - m + 1} \sum_{i=1}^{M-1} C_i^m
\]

(3)

where \( M \) is the number of vectors in \( \{ R_t \} \).

In particular, for finite sequence, \( m = 2, \theta \in [0.1, 0.2] \).

Let \( \tau \) traverses \( \Gamma \), the MSE of \( \{ r_t \} \) is defined as:

\[
MSE(\{ r_t \}) = \{ SE_{\tau} \mid \tau \in \Gamma \}
\]

(4)

2.1.2. Mapping a time series to networks. First, the width of time window is defined as:

\[
\text{width} = \arg \min_{\tau} \left( \left| SE_{\tau} - \text{mid}(MSE(\{ r_t \})) \right| \right)
\]

(5)

where \( \text{mid}(\cdot) \) is the median value of a set.

Second, fragments are coarse-grained to nodes. Let \( R^i \) be the \( i \)th segment, \( \{ R^i \} \) its mean value sequence, \( \alpha_j \) the \( j \)th \( n \)-quantile of \( \{ R^i \} \) for a given catalog number \( n \). Take the first segment \( R^1 \) for example, if \( a_{j-1} < R^1 \leq a_{j,1} \), then fix \( MS_i = i \). By traversing all the pregiven digital features, \( R^i \) is mapped into a multi-symbol \( MS^1 = [MS_1, \cdots, MS_m] \). The remaining can be done in the same manner, thus \( \{ R^i \} \) are mapped into a multi-symbol sequence \( \{ MS^1, MS^2, \cdots, MS^i, \cdots \} \). For convenience, we denoted its unique set as \( \{ \text{node}_i \} \). and use \( g : R^i \to \text{node}_i \) to represent the map from time series segment \( R^i \) to coarse-grained node \( \text{node}_i \), that is, \( \text{node}_j = g(R^i) \).

Finally, for two adjacent node \( f(R^i) \) and \( g(R^{i+1}) \), if there is not a direct edge from \( g(R^i) \) to \( g(R^{i+1}) \), add it and set its weight to 1. If such an edge exists already, update its weight by adding 1. By traversing all values of \( i \) and repeat this process, \( \{ r_t \} \) is mapped to a complex network.
2.2. Network measurements

For a complex network, some measurements were used to quantify its different features. In this paper, 15 measures were used for EEG-based emotion assessment. They include number of nodes or edges, graph density, average of out-degree, standard variance of out-degree, cross entropy of out-degree. Besides, the above out-degree can be replaced by out-strength, betweenness or cluster coefficient. Some of evaluation metrics are listed in Table 1.

Table 1. Measures of networks.

| Name                  | Description                                                                 |
|-----------------------|-----------------------------------------------------------------------------|
| Graph density         | $\frac{2 \cdot \text{num}_{\text{edges}}}{\text{num}_{\text{nodes}} \cdot (\text{num}_{\text{nodes}} - 1)}$ |
| Cross entropy of out-degree | $-\sum_j \left[ \frac{1}{\sum_i \exp\left(k_j^{\text{out}} - \max\left\{ k_i^{\text{out}} \right\} \right)} \log \left( \frac{\exp\left(k_j^{\text{out}} - \max\left\{ k_i^{\text{out}} \right\} \right)}{\sum_{i} \exp\left(k_j^{\text{out}} - \max\left\{ k_i^{\text{out}} \right\} \right)} \right] \right]$ |
| Betweenness           | $\sum_{m\neq i, n \neq i} \frac{\text{path}_{m,n}(i)}{\text{path}_{m,n}}$, where $\text{path}_{m,n}$ is the total number of the shortest paths between node$_m$ and node$_n$, and $\text{path}_{m,n}(i)$ is the number of those paths that pass through node$_i$. |
| Cluster coefficient    | $\frac{2c_i}{n(n-1)}$, where $n$ is the number of neighbours of node$_i$, and $c_i$ is the number of edges among these neighbours. |

2.3. EEG-based emotion assessment

In this subsection, we introduce some details of our approach which includes data pre-processing, EEG map construction and emotion assessing based on convolutional neural network.

For each EEG channel, a bandpass frequency filter should be applied at first. It is generally believed that Gamma wave is very important for learning, memory and information processing. Among them, 40 Hz Gamma wave is the key to the combination of sense and perception. We use an 8-order FIR bandpass filter with a passband of 30 Hz to 50 Hz. Then, calculate width by Eq. (5) for each sequence, and let the average be the window width for all of filtered time series. Four digital features, that mean values, standard variance, range and volatility, are used to coarsen fragments, and the catalogue number is 10. Constructing complex networks and calculating the values of static measurements as described in 2.1. and 2.2..

For each measure, a corresponding EEG map was constructed according to the electrode position, and the missing position was complemented by zero. Take the EEG cap of the international 10-20 system in 62 channels for example, the electrodes position is shown in Figure 2. The corresponding EEG map is shown in Figure 3.
Obviously, for each subject, it is impossible to wear a EEG cap in exactly the same position every time. Considering the spatial information of the electrodes will help to improve the accuracy of the results, a convolutional neuronal network (CNN_E) is constructed to assess emotion from EEG map. Similar to the classical face recognition, we adopt three convolutional layers to extract features, The 1st layer extracts edge information, the 2nd layer combines edge structure, the 3rd layer integrates global image information. Since EEG map is a 9*9 image, after a few tests, we found pool layer reduces accuracy. To enhance generation ability, we add dropout and normalization layer in every convolutional layer. At last, we use relu function as the activation function, and add elementary inputs output, classification layers, we construct a multi-layers structure CNN_E. In short, it includes a input layer, a fully connected layer along with a dropout layer, a softmax layer, a classify output layer, three convolutional layers. Besides, batch normalization and dropout methods are utilized in every convolutional layer. See Figure 4.

3. Data experiment and analysis
SEED (SJTU Emotion EEG Dataset) [21] contains subjects' EEG signals when they were watching films clips. The film clips are carefully selected in same time duration about 4 minutes and reflect positive, negative, and neutral emotion. There are totally 15 trials for each experiment in which fifteen Chinese subjects participated. The detailed protocol is shown in Figure 5. SEED is a collection of EEG dataset provided by the BCMI laboratory in Shanghai Jiao Tong University.

Figure 2. EEG cap [21].

Figure 3. EEG map.

Figure 4. The structure of CNN_E.

Figure 5. Collection flow chart [18].
ESI NeuroScan platform with 62-channel electrodes according to the international 10-20 system used as the data collection facility. The original EEG signals was recorded at a sampling frequency of 1000Hz, and then downsampled to 200Hz so as to provide downloads. The database includes 3 experimental records of 15 subjects (the interval between adjacent experiments of the same subject is no less than one week), each group of data includes 62 electrodes EEG signal records, about 40,000 data for each electrode. While 15 subjects were watching Chinese movie clips (5 film clips in each of the three types of emotional, each fragment length is about 4 minutes with 1 minute interval between the two pieces), ESI NeuroScan platform recorded the EEG signals, then manually intercepted the corresponding data of each clip and added a label.

Some parameters in CNN_E, such as the number of filters in each convolutional layer, or dropout rate, have not been decided yet. Ten-fold test is a common method to optimize structure parameters. For the sake of simplification, here we only showed how to choose the number of convolutional kernels(\(n_{ck}\)) in the first convolutional layer by nine-fold cross validation. Take the range of \(n_{ck}\) in the first convolutional layer be \([200,\ldots,210]\) as an example. Since there are 225 datasets for each kind of emotion, the data was randomly divided to 9 groups (each group has 45 datasets) for convenience. The training parameters are show in Table 2.

| Method      | Learning rate | Drop rate | L2 regularization coefficient | MiniBatchSize | MaxEpochs |
|-------------|---------------|-----------|-------------------------------|---------------|-----------|
| Adam        | 1e-4          | 50%       | 1e-6                          | 128           | 500       |

In each test, take one group as the test dataset, other 8 groups as the training set. The effects of different CNN_E are measured by the average of the classification accuracy on the test set. The accuracies of different groups which are used as test set are shown in Table 3.

| \(n_{ck}\) | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Average |
|------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 200        | 0.78    | 0.82    | 0.82    | 0.78    | 0.86    | 0.74    | 0.78    | 0.82    | 0.78    | 0.7978  |
| 201        | 0.80    | 0.86    | 0.78    | 0.78    | 0.82    | 0.66    | 0.70    | 0.78    | 0.86    | 0.7822  |
| 202        | 0.78    | 0.82    | 0.84    | 0.76    | 0.82    | 0.78    | 0.78    | 0.78    | 0.80    | 0.7956  |
| 203        | 0.72    | 0.84    | 0.74    | 0.82    | 0.80    | 0.70    | 0.84    | 0.80    | 0.78    | 0.7844  |
| 204        | 0.76    | 0.88    | 0.82    | 0.74    | 0.78    | 0.80    | 0.76    | 0.82    | 0.88    | 0.8044  |
| 205        | 0.86    | 0.82    | 0.80    | 0.76    | 0.78    | 0.82    | 0.82    | 0.80    | 0.88    | 0.8166  |
| 206        | 0.74    | 0.80    | 0.76    | 0.68    | 0.78    | 0.76    | 0.80    | 0.76    | 0.80    | 0.7644  |
| 207        | 0.74    | 0.84    | 0.84    | 0.76    | 0.78    | 0.80    | 0.74    | 0.74    | 0.80    | 0.7822  |
| 208        | 0.78    | 0.84    | 0.76    | 0.74    | 0.84    | 0.78    | 0.78    | 0.78    | 0.86    | 0.7956  |
| 209        | 0.80    | 0.78    | 0.78    | 0.76    | 0.72    | 0.74    | 0.76    | 0.76    | 0.86    | 0.7733  |
| 210        | 0.78    | 0.86    | 0.78    | 0.72    | 0.82    | 0.76    | 0.72    | 0.82    | 0.88    | 0.7933  |

The average accuracy of the EEG Feature-based Classifier (EFC) in [18]listed below for comparison. EFC is based on some sequence features of EEG data, such as PSD, differential entropy (DE), differential asymmetry (DASM), rational asymmetry (RASM) and DE difference between frontal and posterior electrodes (DDFP), and the classification task is implemented by deep belief network. Table 4 shows that the average accuracy of EFC based on the same Gamma wave data. Compare to the results in [18], our approach has a slight comparative advantage. Since the best performance of CNN_E is 81.66%, and most are more than the maximal accuracy 79.19% of EFC. Besides, the results of [19] and [20] are listed below in Table 5. CNN_E has better performance too.
Table 4. Average accuracy of EFC with Gamma wave.

| Feature | PSD  | DE   | DASM | RASM | DDFP |
|---------|------|------|------|------|------|
| Accuracy | 63.42% 79.19% 70.06% 68.22% 72.27% |

Table 5. Average accuracy of AE and PSD.

| Method | AE[19] | PSD(CNN)[20] |
|---------|--------|---------------|
| 8 layers | 57.75% | 58.06% |
| 9 layers | 58.06% | 59.03% |
| 10 layers | 73.32% | 80.86% |
| CNN-2 | 77.90% |
| CNN-5 | 77.90% |
| CNN-10 | 77.90% |

4. Conclusion and discussion

A new method of mapping time series to complex network is presented in this paper. Our approach consists of 3 parts: dividing a time series into segments with MSE; coarse-graining segments into nodes based on the distributions of several statistics information; constructing a transition networks as the complex network paradigm of the time series. Based on some static network character measures and the convolutional neural network, we provided an EEG-based emotion assessment method, CNN_E. The simulation on SEED dataset shows that CNN_E is more accurate than some common EEG feature-based Classifier, such as EFC, AE and PSD (CNN). Since there is a degree of correlation between some network measurements, one of the key future works is data compression and redundant removing. Besides, the optimization of the structure of CNN_E helps increase efficiency of emotion assessment too.

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