Multi-modal EEG Online Visualization and Neuro-Feedback

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Abstract. Brain computer interface (BCI) is a communication pathway between brain and peripheral devices, which is promising in the field of rehabilitation and helps to improve the life quality of physically challenged people. Analysis of EEG signal is essential in non-invasive BCI system. However, because of EEG signal's low signal-to-noise ratio and huge amount of data, signal analysis function in current BCI systems is rarely available online, which is inconvenient for system adaptation and calibration, as well as comprehension of data's characteristics. To address the problem, this paper presents two features that are suitable for online visualization. Rhythm power indicates active brain region, and filtered ERSP (Event related spectrum power) is a substitute for original ERSP which provides information in signal's frequency domain. Moreover, visualization of CSP (Common Spatial Pattern) feature is also realized which serves as an indicator of epochs' quality.

Keywords: BCI, EEG, Visualization, ERSP, CSP.

1   Introduction

Brain Computer Interface (BCI) is a communication pathway between brain and peripheral devices making use of brain neural processes, which is independent of the normal output of brain activities, such as movements of muscle tissues. BCI system can be widely used in the rehabilitation of diseases and trauma, and help to improve life quality of physically challenged people. Electroencephalography (EEG) based non-invasive BCI system depends on analysis of the EEG signal patterns under particular tasks of thinking and imagination. Compared with invasive BCI systems, non-invasive ones are safer and easier to apply.

Current BCI systems transform the classification results directly into control commands, and functions of data analysis is only available offline, which leads to poor user interface. Visualization of EEG features provides more intuitive interpretation of EEG signals. With visualization techniques, BCI users would have a better idea of the characteristics of the current signals and how the classification methods are applied to the data, which is useful for system adaptation and calibration. To establish feedback of BCI system to the users, it

will bring benefits to have online visualized features on BCI system's interface. This paper presents visualization techniques that make the EEG signals more comprehensible in realtime.

The rest of the paper is organized as follows: Section 2 introduces two methods extracting features from signals. Section 3 defines some features of EEG signals to be visualized and describes the realization of an online system. Section 4 depicts an experiment for the online visualization and provides interpretations of the visualized features. Section 5 provides the conclusion.

2   Information Extraction for Multi-modal Visualization

Visualization of EEG signal focuses on the extraction of the signal's distribution over frequency domain and space domain. Wavelet transform is performed to obtain a signal's frequency information with respect to time. And common spatial pattern (CSP) is a method widely used in BCI field to find a subspace of brain region for feature extraction and pattern classification.

2.1   Wavelet Transform

Since EEG is a non-stationary signal, frequency analysis using Fourier transform is unable to investigate changes in frequency domain while time elapsing. Wavelet transform can be used to resolve this dilemma. Morlet wavelet is regarded as the best wavelet for EEG time-frequency domain analysis, for which the relation between the scale and frequency is:

$$a = \frac{F_c}{fT}.$$ (1)

where F_c is the center frequency, T is the sampling period.[1][2]

2.2   Common Spatial Pattern (CSP)

CSP is a common feature extraction technique in BCI system. This algorithm is usually applied to find directions in which variation of one class's data is maximized and variation of the other's is minimized. Greater variation indicates higher signal power, and vice versa. According to the CSP algorithm[3][4], a spatial filter consisting of the eigen-vectors with the largest and the smallest eigen-values of a generalized eigen-value problem then can be applied to original data for further classification:

$$W = [w^*_{max1}, w^*_{max2}, \ldots, w^*_{maxL/2}, w^*_{min1}, w^*_{min2}, \ldots, w^*_{minL/2}]^T,$$ (2)

where L is the dimension of the subspace. The variances of filtered data in each dimension are the feature of an epoch.

3   System Realization

3.1   Preprocess

EEG signals are of significant frequency domain characteristics. Since EEG signal power in some specific frequency ranges varies when different movements are imagined, band-pass filter is applied to filter out irrelevant frequencies. Generally, alpha (8-13Hz) and beta (14-30Hz) ranges are used in movement imagination experiments. In some cases, a wider range helps to achieve better effect.

3.2   Characteristic Calculation

Event Related Spectrum Power (ERSP). ERSP is a measure of the power in signal with respect to channel, time and frequency. Let X_e be the epoch e's coefficient of the wavelet transform at channel c, time t and frequency f. Then ERSP can be defined as[5]:

$$ERSP(c,t,f) = \frac{1}{n}\sum_{e=1}^{n}|X_e(c,f,t)|^2 \,. \tag{3}$$

This measure is used to indicate the average signal power at channel c, time t and frequency f. When dealing with online system, only current epoch is processed and visualized, so the size n of the epoch set reduces to 1. Let the number of one epoch's time steps be N_t, and the number of frequency steps be N_f. An N_f by N_t matrix ERSP(c) can be used to represent the ERSP information for each channel. Thus, each channel's ERSP can be visualized by color-scaling the elements of matrix ERSP(c).

Rhythm Power (RP). Rhythm power is a measure of signal power with respect to channel and time over a frequency range, which can be defined as:

$$RP(c,t) = \sum_{f} ERSP(c,t,f) \,. \tag{4}$$

Compared with ERSP, Rhythm power eliminates detail information on frequency steps and considers an entire frequency band as a whole. To display the rhythm power on a head model, the rhythm power RP(c,t) is extracted from one time step t for all of the channels. Making use of the knowledge of the electrodes' position, rhythm power for each time step is interpolated and color-scaled. After being mapped onto a head model, rhythm power reflects the active brain region for each time step.

Common Spatial Pattern (CSP) Feature. CSP feature are extracted from original data as described in section 2.2. This feature is usually organized in the form of a vector, whose dimension equals the number of selected eigen-vectors in (2). However, since this is usually a vector of high dimension, it is difficult to fully visualize the features. Principle component analysis (PCA) can be employed to mapping these feature into a lower space.

Filtered ERSP. Wavelet coefficient $X_e(c, f, t)$ in (3) is a function of channel (electrode) c. Thus, combining wavelet coefficients of all channels at a time step gives a vector over the space of channels. Since CSP algorithm provides the subspace that has most significant difference between each class's signal-powers, applying the CSP spatial filter to the wavelet coefficient vectors gives the vectors' projection in a lower dimension space where differences between each class are more significant.

Given wavelet coefficient $X_e(c, f, t)$, the vector in the channel space is:

$$V_{ori}(t, f) = [X_e(c_1, f, t), X_e(c_1, f, t), \cdots, X_e(c_N, f, t)]^T. \tag{5}$$

Applying the CSP projection matrix W in (2) to the original wavelet coefficient vector in (5) gives the projection of the original vector in the CSP subspace:

$$V_{proj}(t, f) = W V_{ori}(t, f). \tag{6}$$

whose each elements is $X_e(w_i, t, f)$, where w_i indicates that $X_e(w_i, t, f)$ is corresponding to the ith row-vector of the CSP projection matrix W. Thus filtered ERSP is:

$$ERSP(w_i, t, f) = \frac{1}{n} \sum_{e=1}^{n} |X_e(w_i, f, t)|^2. \tag{7}$$

Visualization of filtered ERSP of each channel is the same as that of ERSP, except that the channels of ERSP here are directions of the spatial filter defined by CSP algorithm, i.e., w_i^* in (2). Moreover, since an online system requires more explicit indicators, an auxiliary chart is also provided to show the average ERSP for each channel:

$$\overline{ERSP}(c) = \frac{1}{T \times F} \sum_t \sum_f ERSP(c, t, f). \tag{8}$$

where T and F are the number of time steps and frequency steps.

4   Experiment and Evaluation of Visualization

To evaluate the features mentioned in this paper, we have realized an online system and did an experiment of body movement imagination. In the training stage of our experiment, an arrow is displayed and the subject imagined his or her corresponding movement of left or right arm. The subject's EEG signal is recorded as training set. After training the model using CSP algorithm and SVM, the subject imagines the movement of left or right arm, while his or her EEG data is visualized on screen. We will figure out how the frequency and space domain characteristics are demonstrated in the visualizations.

4.1   ERSP Feature

In Fig. 1 are two visualized ERSPs of 60 one-second-length epochs at C4, which belong to different classes. These two images are the color-scaling result of the

matrix defined by (3) where n=1. The horizontal axis is of time t and the vertical one is of frequency f. Since it is actually the average of ERSP over an epoch set, difference between them is significant. According to the color difference in Fig. 1, these signals of different classes have different signal power in the selected frequency band, especially at the frequencies around 12Hz.
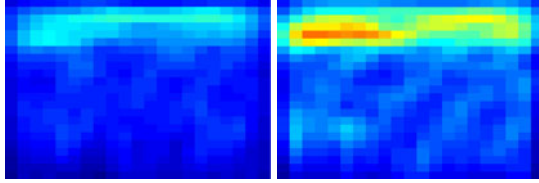

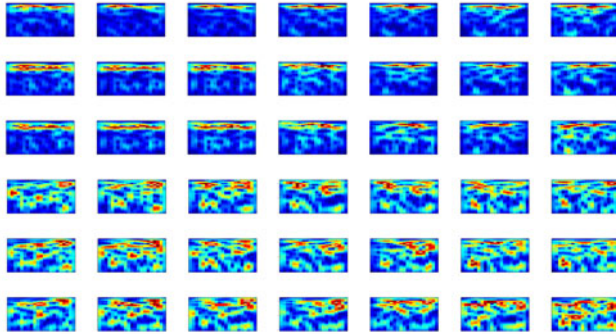**Fig. 1.** ERSP of 60 one-second-length epochs at C4 channel

Fig. 2. Single epoch's (one-second-length) ERSP of 21 channels associated with movement imagination area. The first three rows are of an epoch belonging to class 1 and the other three rows are of an epoch belonging to class 2.

However, for an online system, where only the current epoch is available, it is difficult to tell which class the epoch belongs to according to the ERSP images, even if more channels are provided, as shown in Fig. 2. In Fig. 2 is 21 channels' ERSP related to movement imagination brain region. The first three rows are of an epoch belonging to class 1 and the other three rows are of an epoch belonging to class 2. Each small chart in the figure is the same color-scaling result as Fig. 1, except that only a single epoch is used. When only one channel is provided, the difference between them is too subtle to be intuitive. When all the channels is provided, the information comes in abundance, and observers' capability of perception is easily overwhelmed, especially in an online system, where these charts change all the time. This is the motivation of finding methods to extract information from ERSP.

4.2   CSP Feature

The last row of Fig. 3 shows a bi-class model, as well as three epochs classified by the model. Different colors represent data of different labels in training set, which also indicate the model used for classification. The current unlabeled datum is a green dot in the chart. By observing the position of the current data, one can get a general idea of the quality of this epoch. When the dot is in the overlapping region of classes in training set, it is hard to determine to which class it should be classified, as in the third chart in that row. On the contrary, when it is in a region where almost all the training data is of one class, this epoch is definitely belong to that class and is of high quality, as in the other two charts in that row.
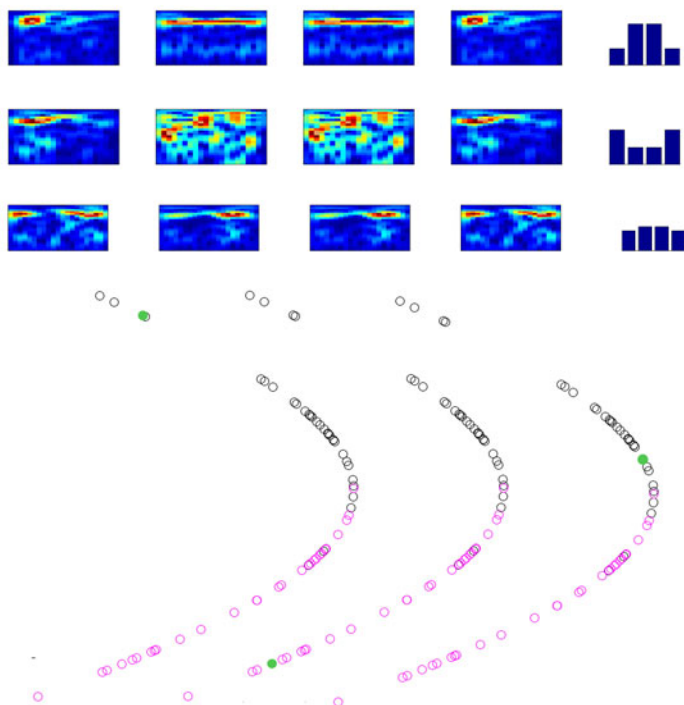

Fig. 3. Filtered ERSP and the corresponding principle component of CSP

4.3   Filtered ERSP Feature

Filtered ERSP is the solution our system uses to make the frequency domain characteristics of a single epoch comprehensible. For the same epoch in Fig. 2, the associated filtered ERSP is in Fig. 3. The signal power in different channels of filtered ERSP is distinguishable between classes, as demonstrated by the auxiliary chart on the right. For class 1, the signal power in the second and the third channel is greater than the other two, and vice versa. This observation is intuitive when running the online system.

In Fig. 3, visualization of the corresponding CSP is provided to indicate the quality of this epoch. The left one is for class 1 and the middle one if for class 2. An additional epoch is also visualized in Fig. 3 to show the overlapping case. This epoch's signal power varies little among four channels of filtered ERSP.

4.4   Rhythm Power Feature

The classification of EEG signals bases on the fact that different imagination of movements leads to different active brain regions. The rhythm power is provided in the system to give an idea of the active brain regions. Fig. 4 shows the rhythm power of two different classes. The deeper in color, the higher signal power in that region. According to Fig. 4, these two classes is characterized by different active regions.
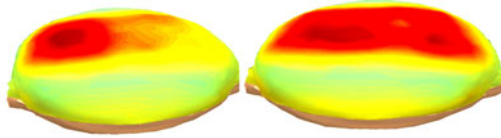
Fig. 4. Visualized rhythm power of two epoches belonging to different classes

5   Conclusion

This paper have discussed a general framework of EEG data visualization. A number of methods exploring basic features in EEG such as ERSP, are discussed. We proposed two techniques, rhythm power and filtered ERSP, to extract useful ingredient from original ERSP. Filtered ERSP provides information in frequency domain. Considering the significant frequency characteristics of EEG signal, it is useful to have an idea of the details in the signal's frequency domain. Rhythm power gives an idea of active brain region. Since CSP algorithm, which is widely used in BCI systems, aims at finding out a brain region of greatest signal power difference, rhythm power is also useful for comprehension of CSP feature. Moreover, with visualized CSP feature in the system, it is possible to evaluate the current epoch's quality and helps to improve the experiment effects.

Acknowledgement

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