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Feature learning from incomplete EEG with denoising autoencoder

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ABSTRACT

An alternative pathway for the human brain to communicate with the outside world is by means of a brain computer interface (BCI). A BCI can decode electroencephalogram (EEG) signals of brain activities, and then send a command or an intent to an external interactive device, such as a wheelchair. The effectiveness of the BCI depends on the performance in decoding the EEG. Usually, the EEG is contaminated by different kinds of artefacts (e.g., electromyogram (EMG), background activity), which leads to a low decoding performance. A number of filtering methods can be utilized to remove or weaken the effects of artefacts, but they generally fail when the EEG contains extreme artefacts. In such cases, the most common approach is to discard the whole data segment containing extreme artefacts. This causes the fatal drawback that the BCI cannot output decoding results during that time. In order to solve this problem, we employ the Lomb–Scargle periodogram to estimate the spectral power from incomplete EEG (after removing only parts contaminated by artefacts), and Denoising Autoencoder (DAE) for learning. The proposed method is evaluated with motor imagery EEG data. The results show that our method can successfully decode incomplete EEG to good effect.

1. Introduction

The combination of advanced neurobiology and engineering creates a new pathway, namely a brain computer interface (BCI). The BCI provides a bridge connecting the human brain to the outside world [1]. This means that people do not have to rely on the conventional pathway of an intent initialized in the brain being passed to muscles through peripheral nerves, and are able to interact directly with the external environment [2]. Due to the lack of involvement of peripheral nerves and muscles, with the aid of a BCI system, disabled people have been able to restore their abilities of communication [3] and the degenerated motor function [4,5]. During the past two decades, a variety of BCI systems have been created for different applications. These BCI systems are generally divided into two types: active BCI and passive BCI, according to the level of interaction with external stimuli. In the case of a passive BCI, when using a steady-state visual evoked potential (SSVEP) BCI [6], the user may, for example, simply stare at an intended digital number shown on a screen to dial a phone number. When a steady-state flicker is replaced with an occasional flicker, a different type of BCI called P300 can be used to output letters by hierarchical selections [3]. Compared to the passive BCI, the active BCI is more natural. Users can express their intents whenever they want to, rather than according to a predefined timing arrangement or external cooperation, as with the passive BCI. For instance, people with paraplegia can regain movement in a wheelchair by motor imagery [4], or can control a computer cursor in virtual 2D [7] or 3D [8] environments through brain modulation. Moreover, BCI is also used to develop prostheses, with which disabled people can, for example, move an object [9] or drink a cup of coffee [10]. More recently, BCI has been applied to facilitate rehabilitation [11,12]. Besides applications for disabled people, BCI also has promising applications for healthy persons, especially in the field of entertainment. BCI is employed to control video games instead of conventional inputs such as a keyboard and joystick [13]. In this way, healthy people can enjoy the experience of manipulating virtual objects in a manner different from that used in daily life.

From the application point of view, the user experience is very important. This requires smoothness in the manipulation of the BCI system. In order to meet this requirement, the BCI system needs to translate brain activities into output information continuously without any interruption. In other words, this requires all the EEG segments to be present for the decoding. If some of the EEG segments are discarded due to extreme noise contamination, the BCI cannot generate the corresponding output during that

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period. Hence, it would be good to be able to utilize the remaining portion of the affected EEG segment, after only removing the part directly affected by noise. In general, spectral power features are usually utilized to distinguish different motor imageries (e.g., left-hand and right-hand motor imageries) [14–17], as they are considered to be robust for the representation of the contents of motor imageries. If the segment is complete (continuous), the Fourier transform can be well used to transform temporal data points into the spectral domain. This fails in the case of incomplete data, such as an EEG segment with a portion (or portions) of data removed (unevenly spaced). In order still to utilize such segments of EEG with arbitrary portions of data removed and provide users with an experience of smooth manipulation, we employ the Lomb–Scargle periodogram to estimate the spectral power [18,19], and Denoising Autoencoder (DAE) [20,21] based neural network or support vector machine (SVM) [22,23] to predict the classes of motor imageries. The results show that the proposed method is suitable for decoding incomplete EEG in a BCI system.

2. Methodology

We first employed the Lomb–Scargle periodogram [18,19] to estimate band powers from incomplete EEG signals. Next, the extracted features were used to train an unsupervised DAE [20,21] or a supervised SVM with Radial Basis Function (RBF) kernel [22,23]. In the case of DAE, the mapping weights of DAE were used to initialize a neural network. After fine-tuning the weights, this trained neural network was used to recognize the classes of motor imageries. Fig. 1 illustrates the proposed method.

2.1. Lomb–Scargle periodogram

A four-second trial is divided into 25 segments of one-second length with an overlap of 87.5%. A segment is denoted by X, which is N by T matrix, where N is the number of channels, and T is the number of sampling points. The spectral power of each channel time series $y(t_i)$ is estimated by the Lomb–Scargle periodogram [18,19]. The estimated spectral power at frequency Ω_f can be obtained by minimizing the following sum of difference squares:

$$\min_{\substack{\alpha>0 \\ \phi\in[0,2\pi]}} \sum_{i=1}^{T} (y(t_i) - \alpha\cos(\Omega_f t_i + \phi))^2. \tag{1}$$

Let

$$a = \alpha\cos\phi \tag{2}$$

and

$$b = -\alpha\sin\phi. \tag{3}$$

We can then rewrite Eq. (1) as:

$$\min_{a,b} \sum_{i=1}^{T} (y(t_i) - a\cos(\Omega_f t_i) - b\sin(\Omega_f t_i))^2. \tag{4}$$

The optimal parameters $\hat{a}$ and $\hat{b}$ can be obtained through minimizing Eq. (4)

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = R^{-1} r, \tag{5}$$

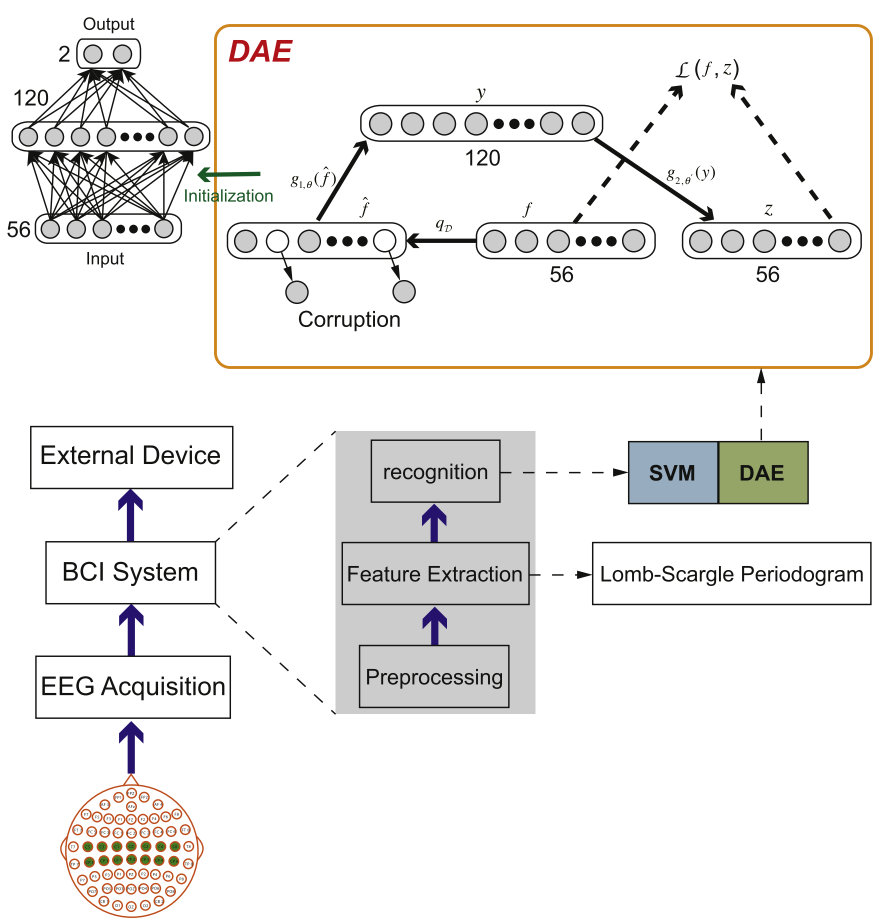

Fig. 1. Schematic depiction of the proposed method. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)