Motor Imagery Classification based on RNNs with Spatiotemporal-Energy Feature Extraction

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Abstract

With the recent advances in artificial intelligence and robotics, Brain Computer Interface (BCI) has become a rapidly evolving research area. Motor imagery (MI) based BCIs have several applications in neuro-rehabilitation and the control of robotic prosthesis because they offer the potential to seamlessly translate human intentions to machine language. However, to achieve adequate performance, these systems require extensive training with high-density EEG systems even for two-class paradigms. Effectively extracting and translating EEG data features is a key challenge in Brain Computer Interface (BCI) development. This paper presents a method based on Recurrent Neural Networks (RNNs) with spatiotemporal-energy feature extraction that significantly improves the performance of existing methods. We present cross-validation results based on EEG data collected by a 16-channel, dry electrodes system to demonstrate the practical use of our algorithm.

Introduction

Robotic control, based on brainwave decoding, can be used in a range of scenarios including patients with locked-in syndrome, rehabilitation after a stroke, virtual reality games and so on. In these cases, subjects may not be able to move their limbs. For this reason, the development of MI tasks based BCI is very important [1]. During a MI task, the subjects imagine moving a specific part of their body without initiating the actual movements. This process involves the brain networks, which are responsible for motor control similarly to the actual movements.

Decoding brain waves is challenging, since EEG signals have limited spatial resolution and low signal to noise ratio. Furthermore, experimental conditions, such as subjects' concentration and prior experience with BCI can bring confounds to the results. Thus far, several approaches have been proposed to classify MI tasks based data but their performances are limited even for the two-class paradigms that involve left and right hand MI tasks [2]. EEG-based BCI normally involves noise filtering, feature extraction and classification. Brain signals are normally analysed in cue-triggered or stimulus-triggered time windows. Related methods include identifying changes in Event Potentials (EPs), slow cortical potentials shifts, quantify oscillatory EEG components and so on [3]. These types of BCI are operated with predefined time windows. Furthermore, the inter- and intra-subject variability cannot be overlooked when finding suitable feature representation model.

Recently, Deep Neural Networks (DNNs) have emerged with promising results in several applications. Their adaptive nature allows them to automatically extract relevant features from data without extensive pre-processing and prior knowledge about the signals [4]. Convolutional Neural Networks (CNNs) have been used to classify EEG features by transforming the temporal domain into spatial domain [5]. However, the CNN structure is static and inherently not suitable for processing temporal patterns. Furthermore, the trend in BCI is to reduce the number of channels and thus construct a sparse spatial representation of the signal, which impedes the effectiveness of CNNs.

To deal with time series data, recurrent neural networks (RNNs) based on Long Short-Term Memory (LSTM) seems to be a better choice since they can preserve temporal characteristics of the signal [6]. In this paper, we propose a novel approach to decoding multichannel EEG raw data based on RNNs and spatiotemporal features extracted from the EEG signal. Appropriate spatiotemporal feature extraction could play an important role in improving learning rate in these DNN. The presented results were based on an EEG dataset acquired using a dry, 16-channels, active electrodes g.tec Nautilus system. Although wet, active electrodes are the gold standard in EEG signal acquisition, they require long preparation times and the conductive gel to reduce skin-electrode impedance, which makes the subjects feel uncomfortable [7]. Dry electrodes make it easier to bring BCI systems from the laboratory to the patients' home but with the challenge of decoding low-quality signals. Therefore, there is a need for the development of more advanced methods for feature extraction and classification.

Methods

Experimental Setup: EEG data were recorded from four healthy participants (one female, three males, 21-24 years old). During the experiment, the subjects were asked to complete a Graz-BCI MI task [8] for two-class (right/left hand, 20 trials/class). Subjects had no previous experience with BCI. A g.tec *Nautilus*, 16-channels dry, *g.Sahara* electrodes, EEG wireless acquisition system was used with active-electrodes placed on the subject's scale according to the standard 10-20 system. Figure 1 (a) shows the original electrodes distribution, while Figure 1 (b) shows the mapping relationship of the spatial distribution of the feature graphs.

Feature Extraction based on spatiotemporal energy characteristics: Three feature representation methods were tested in the experiments. Figure 1 (c) shows the spatiotemporal feature graph. The value of each pixel
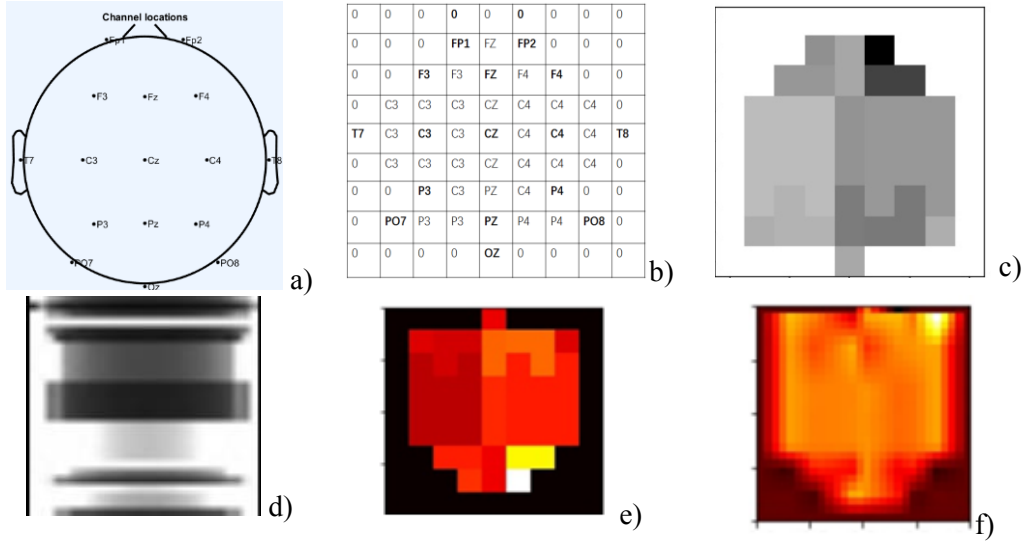
Figure 1. a) 16 channels EEG helmet electrodes distribution, b) spatial distribution of the feature graph, c) Spatiotemporal Feature Graph (ST-FG), d) Time-Frequencybased features across channels and epochs (without spatial information), e) Spatiotemporal-Energy Feature Graph (STE-FG), f) Smoothed Spatiotemporal-Energy Feature Graph (STE-FG).

represents the normalized amplitude of a specific channel during a time epoch. Subsequently, short time Fourier Transform was used to extract Time-Frequency features as shown in Figure 1 (d), represented as a graph. The combination of spatiotemporal characteristics along with energy spectrum has provided the most effective classification features. To construct these features, the band power was used to track amplitude modulation at particular frequencies (8Hz-30Hz) related to motor intention, namely $\mu(7-13Hz)$ and $\beta(13-30Hz)$. In other words, the power spectral intensity was estimated for μ and β band, respectively as $E(\mu)$ and $E(\beta)$. Subsequently, the intensity ratio $p = E(\mu)/E(\beta)$ was used as a classification feature. After normalization, each pixel in the feature graph represents the ratio of energy in each time epoch of every channel, which provides information about the spatiotemporal distribution of energy. Finally, interpolation was utilized to smooth the energy spectral ratio graph, as shown in Figure 1 (f).

RNN Framework for Classification: A RNN based on LSTM is trained to learn features from the sequences of EEG data. LSTM units were employed to construct each RNN layer, since they are less sensitive to the gradient vanishing and exploding problems. The proposed approach is designed to preserve the spatiotemporal and energy information of EEG and to extract features that are less sensitive to noise within each channel.

Results

The proposed method used has been compared with other common approaches in motor imagery classification. The results have been summarised in Table 1. The first column shows results based on Common Spatial Pattern (CSP) for feature extraction and Support Vector Machine (SVM) for classification implemented in Matlab. To improve classification performance, the EEG signals have been pre-processed with a wavelet-based technique to preserve frequencies between 0.1 and 40 Hz and removed physiological noise related to eye blinks [9][10]. The proposed methods have also been evaluated against CNNs, while different features extraction methods are evaluated at the same time.

Table 1. Comparison for the classification accuracy of the motor imagery tasks.

SUBJECTS	CSP/SVM	ST-FG/CNN	STE-FG/CNN	ST-FG/RNN	**STE /RNN**
01	56.5 %	50.9 %	60.1 %	62.5 %	**80.8 %**
02	54.5 %	54.4 %	56.3 %	72.3 %	**88.7 %**
03	52.7 %	55.0 %	57.8 %	58.7 %	**75.6 %**
04	61.9 %	52.1 %	59 .0 %	60.5 %	**80.5 %**
Mean ± std	56.4±4.0 %	53.1±1.9 %	58.3±1.9 %	63.5±6.1%	**81.4 ±5.4%**

Conclusions

Our results show that a RNN classification based on spatiotemporal energy characteristics outperforms both methods based on CSP/SVM and CNNs. Preserving the Spatiotemporal information along with extracting energy features plays a critical role in the overall performance of MI tasks based data classification.

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