DEEP LEARNINIG OF EEG SIGNALS FOR EMOTION RECOGNITION

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ABSTRACT

Emotion recognition is an important task for computer to understand the human status in brain computer interface (BCI) systems. It is difficult to perceive the emotion of some disabled people through their facial expression, such as functional autism patient. EEG signal provides us a non-invasive way to recognize the emotion of these disable people through EEG headset electrodes placed on their scalp. In this paper, we propose a deep learning algorithm to simultaneously learn the features and classify the emotions of EEG signals. It differs from the conventional methods as we apply deep learning on the raw signal without explicit hand-crafted feature extraction. Because the EEG signal has subject dependency, it is better to train the emotion model subject-wise, while there is not much epochs available for each subject. Deep learning algorithm provides a solution with a pre-training way using three layers of restricted Boltzmann machines (RBMs). Thus, we can use epochs of all subjects to pre-training the deep network, and use back-propagation to fine tuning the network subject by subject. Experiment results show that our proposed framework achieves better recognition accuracy than conventional algorithms.

Index Terms— EEG, Emotion Recognition, Deep learning, RBM

1. INTRODUCTION

Emotion classification is an active topic in the past decades. It is the bridge of human and machines, and it is essential for computer to understand the emotion of users as a brain computer interface (BCI) system [1-2]. There are many ways to recognize the emotion, such as facial expression and brain waves. However, it is difficult to recognize emotion from some disabled people based on their appearance, such as autism. Brain signal is an alternative way to access human emotion, which can be acquired in invasive and non-invasive manners. An invasive BCI places electrodes on the exposed surface of a brain using surgical operation, such as an incision into the skull. This is not an acceptable way for most of human beings. The non-invasive way provides a more convenient and favorable way to collect the brain signal, which includes magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), EEG. Especially, EEG exhibits some advantages compared to the other ones due to its better temporal resolution and low cost of setup [3]. The emergence of wireless EEG headsets enable the leisure users to capture the electric potentials through electrodes placed on the scalp.

EEG signals can be used in many applications besides medical purposes, such as games, health care, entertainment system. From the health care perspective, it is meaningful to facilitate the disabled people to manipulate their wheelchair with recognition of EEG signal by learning their patterns. This idea can be extended to ordinary human for driving a car and moving a cursor. As for the functional autism people, it is difficult to communicate with them through conversation or appearance, while the emotional state of these patients plays an important role during their therapy or education. It can also provide valuable insights for their continuous daily monitoring of social behavior.

EEG signals exhibit specific patterns for each emotional state, such as hypnosis, arousal, exercise and concentration. The electrode location of EEG signal acquisition is shown in Fig. 1. After the acquisition of EEG signal, the first step of EEG analysis is the preprocessing, including artifact removal, signal average, output threshold, signal enhancement, and edge detection. The artifact of EEG signals come from the power line electrical noise and muscular activities and blinking of eyes during the signal acquisition [4].

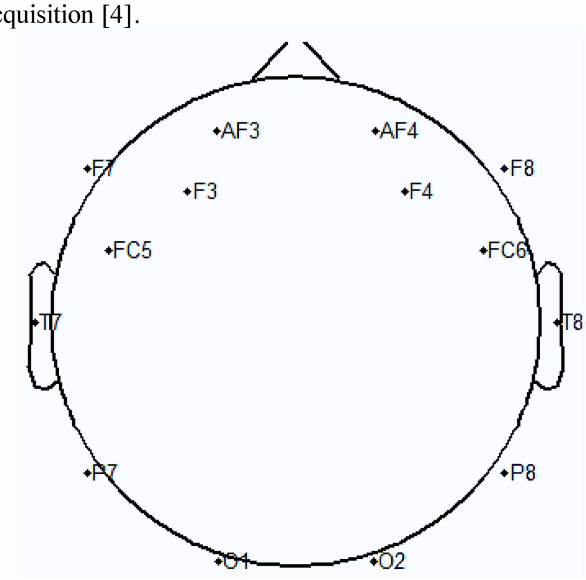


Fig. 1. Electrode placement structure of EEG signal acquisition.

Feature extraction usually plays an important role for high performance classification as well as time reduction. Frequency bands are important factors to be considered according to their efficacy. The change of signal along with the time is another important feature of EEG analysis. Considering these, we should study on the time-frequency feature. The short time Fourier transform (STFT) is a popular method to extract time-frequency feature [5]. However, its high computational time make it difficult to be applied in real time systems. An alternative solution is Hjorth parameter with simpler computation [6-8].

Various machine learning algorithms have been used to recognize emotion of EEG signal, including K-Nearest Neighbor (KNN) [9], Regression Tree (RT) [10], Bayesian Network (BNT) [11], Support Vector Machine (SVM) [12] and Artificial Neural Networks (ANN) [13]. These algorithms are successfully applied to emotion recognition; however, the performance in terms of accuracy is not high enough due to the subject dependency of emotion.

In this paper, we present a deep learning algorithm to simultaneously learn the features and classify the emotions of EEG signal. It differs from the conventional method as we apply deep learning on the raw signal without hand-crafted feature extraction. As we know, the EEG signal is subject dependency, it is better to train the emotion model subject-wise, while there is not much epochs available for each subject. Deep learning algorithm [14] provides a solution with a pre-training way using three layers of restricted Boltzmann machines (RBMs), which is widely used in many applications [21]. Thus, we can use epochs of all subjects to pre-training the deep network, and use back-propagation to tune the network fine subject by subject.

The remainder of this paper is organized as follows. Section 2 describes the emotion recognition of EEG signal based on deep learning. Section 3 applies the above algorithm to our EEG dataset, and presents the experiment results. Finally, we conclude this paper in Section 4.

2. EMOTION RECOGNITION BASED ON DEEP LEARING

Traditional back-propagation method to learn a deep architecture suffers from the poor local optima problem as well as the long learning time. Also, labeled training data is a necessary for back-propagation, which is not satisfied in our EEG analysis due to its subject dependency. Deep learning method [14] provides a solution to address all these problems, which enable us to use unlabeled data to initialize the deep network. The architecture of our deep network is shown in Fig. 2. The EEG signals of 14 channels are unrolled into a vector and fed into the three layers of RBMs, following by the output layer of emotion labels. Three layers of RBMs are first pre-trained using epochs of unspecified labels and subjects. Back propagation is used to fine tuning subject specific deep models by labeled data.

Unlabeled data are easier to be acquired than label data. Thus, we use unlabeled data to pre-training the deep architecture to get initial weights. Through these initial weights that close to a good solution, we are readily to achieve an optimal solution. Restricted Boltzman machine offers an effective pre-training method, which is a two-layer network with stochastic and binary pixels as units. These two layers comprise of pixels of "visible" units and "hidden" units that are connected using symmetrically weighted connections. The RBM model can be represented as an energy model:

$$E(v,h) = -\sum_{i \in visible} b_i v_i - \sum_{j \in hidden} b_j h_j - \sum_{i,j} v_i h_j w_{ij} \quad (1)$$

where v_i and h_j are the binary values of unit i and j, b_i and b_j are their corresponding biases, and w_{ij} is the weight of their connection. The probability of a possible image is assigned according to this energy. Given a training image, we alternately calculate the probability of binary state v_i and hidden units h_j to be set to 1 as follows:

$$p(h_j = 1|v) = \sigma(b_j + \sum_i v_i w_{ij}) \quad (2)$$

$$p(v_i = 1|h) = \sigma(b_i + \sum_j h_j w_{ij}) \quad (3)$$

By updating the states of hidden units and reconstruction of visible units, we can obtain a change in weight by:

$$\Delta w_{ij} = \varepsilon(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{recon}) \quad (4)$$

where ε is the learning rate, $\langle v_i h_j \rangle_{data}$ is the fraction of multiplication of visible and hidden units driven by data, while $\langle v_i h_j \rangle_{recon}$ is the fraction driven by reconstruction images.

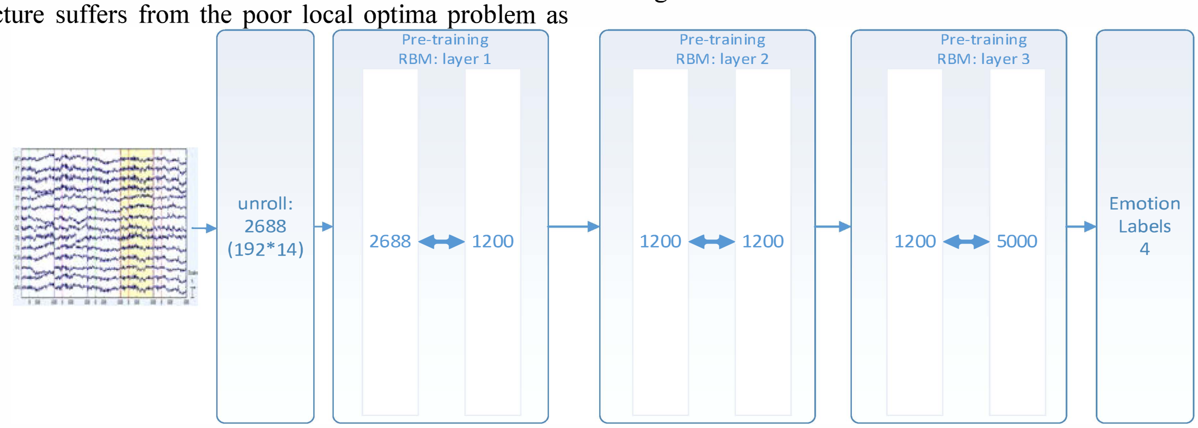
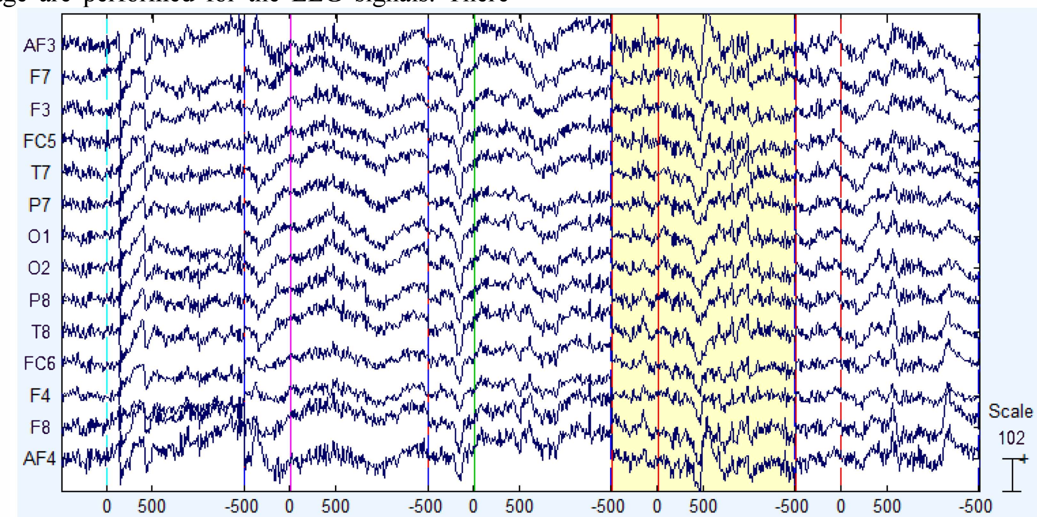


Fig. 2. Architecture of deep learning with three layers of RBM.

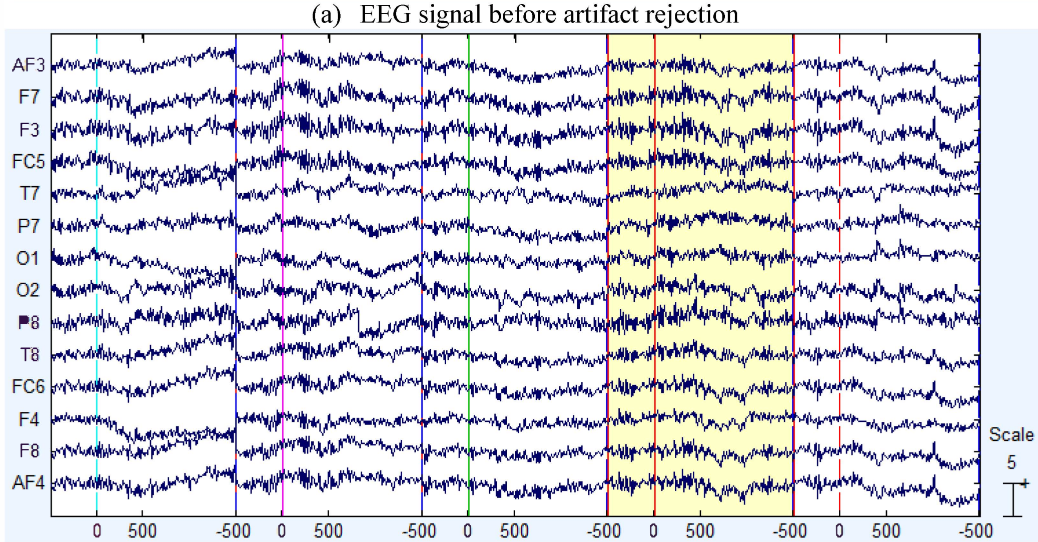
3. METHODOLOGY AND RESULTS

3.1. Preprocessing

We use EEGLAB to preprocess EEG signals, which is an open source platform by SCCN lab [15]. EEGLAB contains a collection of functions for EEG channels and epoch management and visualization. As for the preprocessing, artifact rejection [16], filtering [17], epoch selection, and signals average are performed for the EEG signals. There are 14 channels of EEG signals collected from the EEG headset device [18]. Fig. 3 shows the 14 channels and corresponding signals [19], where Fig. 3(a) presents the artifact incurred by eye blink through Fp1 and Fp2 before the rejection, which is marked as yellow shadow. After the artifact rejection, the eye blink effect is removed as shown in the yellow shadow of Fig. 3(b).



(a) EEG signal before artifact rejection



(b) EEG signal after artifact rejection

Fig. 3. Illustration of artifact rejection of EEG signal.

3.2. Emotion Classification

After the pre-processing was completed, we got the clean EEG signals, which were fed into the deep network without feature extraction. We built our databases with 21 subjects, and 180 epochs of the dimension of 192 for each are collected for each subject. We define four emotions in our experiments: happy, calm, sad, and scared. For each emotion, we collect 45 epochs for each subject.

As we mentioned earlier, emotion classification is subject dependent. Thus, we divide our epochs of each subject into training and test epochs. Considering the deep learning architecture that consists of pre-training and fine tuning, we use epochs of all subjects for pre-training, and subject specific epochs for fine tuning deep model of each subject as shown in Fig. 4. As a result, there are 21 deep models are fine-tuned for each subject based on the initial weights pre-trained by three layers of RBMs. These 21 deep models are applied to their corresponding subjects for tests.

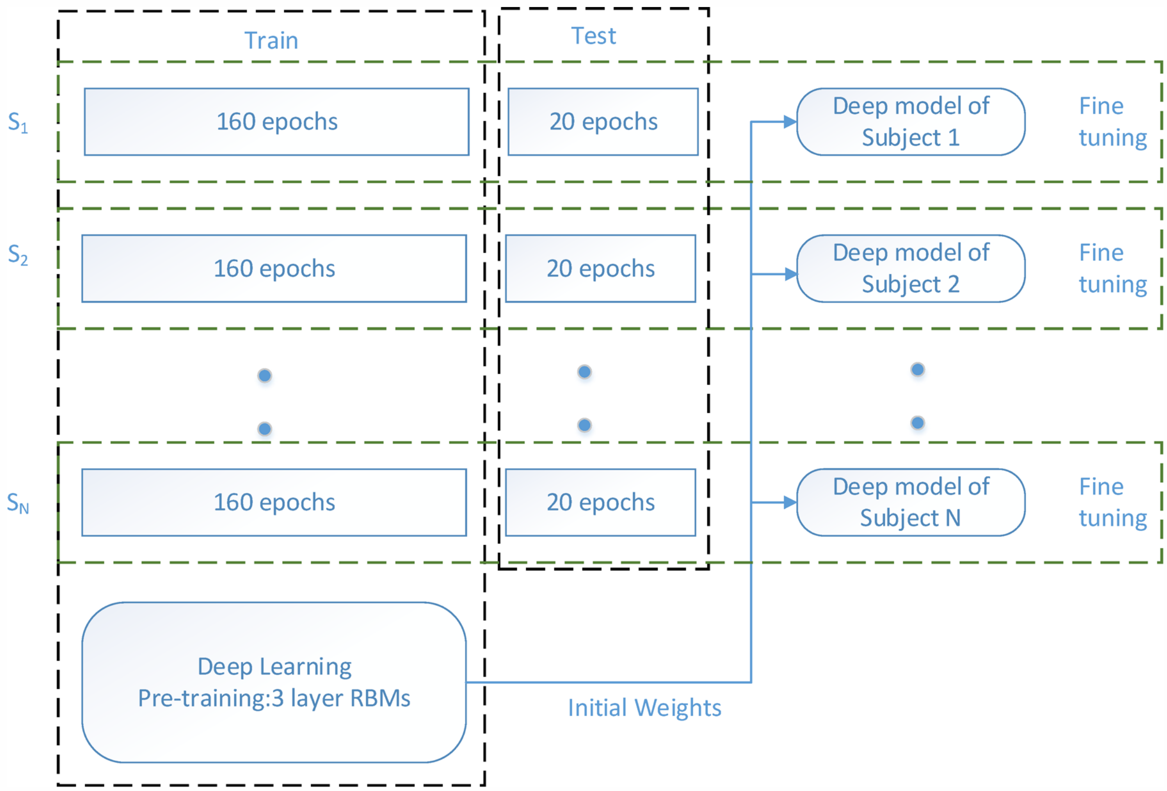


Fig. 4. Experiments method of emotion classification based on deep learning

The pre-training is performed once across all subjects, while the deep model is fine-tuned for each subject based on the initial weights of the pre-training as shown in Fig.4. The emotion recognition accuracies of subjects are shown in Fig. 5. This figure verifies that the emotion recognition is subject dependent as the accuracy varies from subject to subject and exhibits high variance of accuracy.

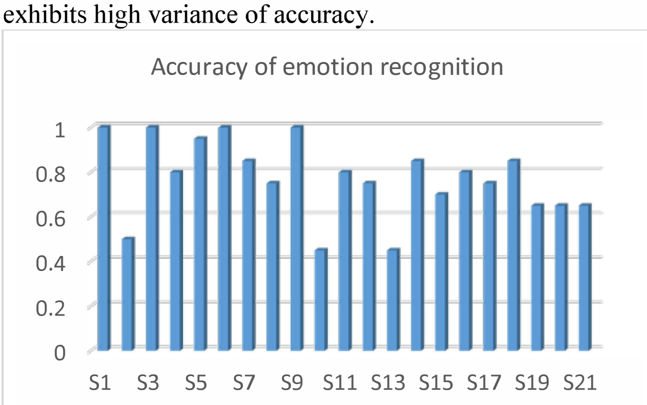


Fig. 5. Emotion recognition accuracy of various subjects.

Cross-validation is used in our experiments, we randomly divide the 180 epochs of each subject into training set of 160 epochs and test set of 20 epochs. This process repeats ten times to obtain an average performance. Table 1 shows the average accuracy of emotion recognition of three comparison algorithms (KNN, SVM, and ANN) and three implementation of deep learning: (1) subject untied: we use 11 subjects for training, and 10 subjects for tests in this implementation; (2) channel selection: it is noted that not every channel are of the same efficacy in terms of emotion recognition accuracy. Six channels are selected as the raw signal, which are channels Fp1, Fp2, C3, C4, F3, and F4 [20]; (3) subject tied: it is the implementation of Fig. 4. Deep models are fine-tuned and tested subject by subject. Table 1 shows that the subject untied implementation does show low performance due to the subject dependency, while the channel selection implementation has comparable performance with subject tied one even the channels are reduced much. As for KNN, SVM, and ANN, we use subject tied protocol, which train and test the algorithm separate by subjects. In this way, the epochs of subjects are not involved with other subjects' training, and have no contribution to other subjects' accuracy. Thus, the subject tied implementation achieved better recognition accuracy than conventional algorithms it compared to, while requires more improvement.

Table 1. Accuracy of emotion recognition of various implementation of deep learning and other algorithms

Algorithm	Accuracy (%)
KNN	51.3
SVM	60.8
ANN	60
Subject untied	28.6
Channel selection	57.2
Subject tied	68.4

4. Conclusion

A deep learning architecture is proposed to learn and classify the emotions of EEG signal. It differs from the conventional method*s* as we apply deep learning on the raw signal without hand-crafted feature extraction. Deep learning algorithm provides us a solution with a pre-training way using three layers of restricted Boltzmann machines (RBMs). Thus, we can use epochs of all subjects to pre-training the deep network, and use back-propagation to fine tuning the network subject by subject. Experiment results verify that emotion recognition of EEG signal is subject dependent, and our subject tied implementation of deep learning achieves better recognition accuracy than conventional algorithms.

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