Implementation of EEG Emotion Recognition System Based on Hierarchical Convolutional Neural Networks

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Implementation of EEG emotion recognition system based on hierarchical convolutional neural networks

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Abstract. Deep Learning (DL) is capable of excavating features hidden deep in complex data. In this paper, we introduce hierarchical convolutional neural networks (HCNN) to implement the EEG-based emotion classifier (positive, negative and neutral) in a movie-watching task. Differential Entropy (DE) is calculated as features at certain time interval for each channel. We organize features from different channels into two dimensional maps to train HCNN classifier. This approach extracts features contained in the spatial topology of electrodes directly, which is often neglected by the widely-used one-dimensional models. The performance of HCNN was compared with one-dimensional deep model SAE (Stacked Autoencoder), as well as traditional shallow models SVM and KNN. We find that HCNN (88.2%±3.5%) is better than SAE (85.4%±8.1%), and deep models are more favorable in emotion recognition BCI (Brain-computer Interface) system than shallow models. Moreover, we show that models learned on one person is hard to transfer to others and the individual difference in EEG emotion-related signal is significant among peoples. Finally, we find Beta and Gamma (rather than Delta, Theta and Alpha) waves play the key role in emotion recognition.

Keywords: Emotion Recognition; EEG; Deep Learning; HCNN; Brain Wave

1 Introduction

The computational models of emotion is one of the major interests for psychologists, because they might help them understand the mechanism of emotion processing. The emotion recognition system is also an exciting researching topic for computer scientists and engineers, for such system is vital in multiple applications, e.g. workload estimation [1], driving fatigue detection [2], and BCI equipment [3].

There are many physiological signals to help us recognize the emotion state of one subject, which could be divided into two categories. One is called the ‘external clues’, e.g. facial expression and gesture [4]. Signals of this kind are highly related to the personal habit of subjects, and thus could not be universally used. The favorable physiological signals should be able to describe across different cultures and language backgrounds [5]. The second kind of signals are called the 'internal clues', and among which, electroencephalograph (EEG) is widely used. EEG is reliable for emotion recognition, because it has high accuracy and relatively objective evaluation in comparison with the 'external' ones. The great assumption is that the brain contributes, or even determines the emotion state of one person. EEG devices often have multiple channels (electrodes) to collect electric potentials from different positions. The electrodes are either implantable (i.e. capable of being implanted in living brain tissue through operation) or non-implantable. The former has higher signal-to-noise ratio (SNR), but not fit to the daily use. The latter collects signals on the scalp, and it is noninvasive and wearable. That is favorable to commercial BCI systems (the application demands require the signal-collecting method to be as convenient as possible, e.g. the recent dry EEG equipment even omits the conductive paste). However, the SNR is low. The useful information for emotion recognition is submerged in the noise. Therefore, traditional feature-extraction methods (e.g. PCA and Fisher Projection) are insufficient to excavate patterns hidden deep in EEG signals, because the cost of traditional feature selection methods increases quadratically with respect to the number of features considered [6]. We need more powerful models to learn the most efficient features in the EEG signal.

Since the work of Hinton and Krizhevsky in 2012 [7], Deep Learning (DL) has dominated the machine learning research, and becomes the absolute winner in complex tasks such as image classification [8] and machine translation [9]. DL is capable of learning features automatically, because the DL structures trained under explicit goals (minimize the classification error) in turn possess powerful representational ability. The most important structures include HCNN [7], SAE [10], and DBN [11].

We could analyze EEG signal either in the time domain or in the frequency domain, or the combination of them. The time-domain analyze usually brings heavy computational burden, and not resistant to noise. Consequently, researchers tend to seek for the emotion-related patterns in frequency or time-frequency domain. There are five bands of brain wave that interest the researchers the most: Delta, Theta, Alpha, Beta and Gamma. Delta wave (1-3 Hz) is the slowest 'sleep wave'. Theta wave (4-7 Hz) is believed to be active in light meditation and sleeping. Alpha wave (8-13 Hz) is the 'deep relaxation wave', which is linked with our sense of happiness. Beta wave (14-30 Hz) is the 'waking consciousness and reasoning wave'. Gamma wave (31-50 Hz) has the highest frequency, and little is known about it. Initial research shows Gamma waves are associated with bursts of insight and high-level information processing. Li and Lu [12] proposed that Gamma wave was suitable for EEG-based emotion classification with emotional still images as stimuli. Therefore, Delta, Theta and Alpha might be favorable in resting-state emotion reading. Beta and Gamma waves are tightly-related to rational activities, and thus good for task-evoked emotion reading.

Fourier power might be a choice to characterize the signals, but EEG signal is not a stationary process. Hadjidimitriou et al. [13] employed three kinds of time-frequency distributions (spectrogram, Hilbert-Huang spectrum and Zhao-Atlas-Marks transform) as features to classify ratings of liking and familiarity. Yang Li et al. [14] applied wavelet energy to compensate for the influence of non-stationary character. Baoliang Lu et al. [5] used DE as features to classify three emotion states: positive, negative and neutral. They organized features in one-dimensionality and used DBN (Deep Belief Networks) to realize the classifier, and then they investigated the critical frequency bands and channels. The accuracy they obtained was as high as 86.08%.

In this paper, we extract DE features in a movie-watching task, and in order to maintain the information contained in the positional relationship between the electrodes, we organize them as two-dimensional maps to train HCNN classifiers on each frequency bands. The performance is compared with other models. We will also illustrate the relationship between the five frequency bands and the emotion states.

2 Methods

2.1 Short-time Fourier Transform and Differential Entropy

Fourier Transform (FT) is often used to analyze the frequency configuration of a time-domain signal, and it is widely used in EEG decomposition. However, the FT operation assumes that brain wave activities are stationary, which is a false hypothesis apparently. Therefore, the time series should be cut into small time segments, and within each segment, the brain electric activities are approximately considered as stationary. The idea is called the Short-time Fourier Transform (STFT). STFT decomposes a function of time (EEG signal) into the frequencies that make it up at fixed time intervals. The calculation formulation of STFT is:

$$\mathrm{X}(\tau,\omega) = \int_{-\infty}^{\infty} x(t)\,\omega(t-\tau)e^{-j\omega t}dt \tag{1}$$

Where $x(t)$ is the original signal, $\omega(t)$ is the window function. Hanning Window usually emerges in applications that require low aliasing and less spectrum leakage.

DE [15] is the extension of the Shannon entropy (1), which is an efficient definition of the complexity of a discrete random variable (i.e. if we want to know a random variable thoroughly, how much information do we need). The more information contained in a time series, the more complex it is. DE could be simply understood as the continuous edition of Shannon entropy, and thus a good kind of feature to characterize EEG time series.

$$\mathrm{h(x)} = -\sum_{i=1}^{N} p(x_i)\log(p(x_i) \tag{2}$$

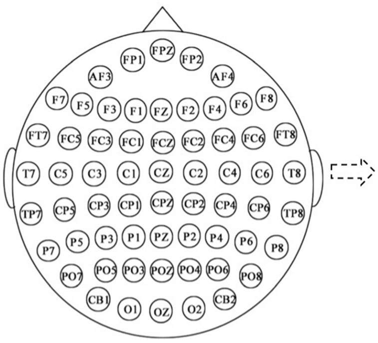
$$\mathrm{h(x)} = -\int f(x)\log(f(x))dx \tag{3}$$

If the random variable obeys the Gaussian distribution $\mathrm{N}(\mu,\sigma^2)$, the differential entropy in (3) can simply be calculated by the following formulation:

$$\mathrm{h(x)} = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}}\exp\frac{(x-\mu)^2}{2\sigma^2}\log\frac{1}{\sqrt{2\pi\sigma^2}}\exp\frac{(x-\mu)^2}{2\sigma^2}dx = \frac{1}{2}\log 2\pi e\sigma^2 \tag{4}$$

2.2 Two-dimensional Feature Organization

In order to maintain the information of EEG placement as much as possible, we organize features (DE in this paper) extracted from 62 channels as two-dimensional maps at a time interval of one second. The configuration of the DE map is illustrated in Fig. 1. In this paper, we organize the DE features in such configuration to feed HCNN for training. However, the map size is two small and the 'pixel values' are too 'concentrated', so we introduce sparsity to generate sparse DE maps that are more suitable for HCNN dispose: all-zero rows and columns are added on alternate rows and columns. All-zero frames are also added on the four edges of maps to maintain patterns hidden in peripheral electrodes. The detailed operation of sparsity will be discussed further. After the sparse operation, the DE map is 20*20, and the size is sufficient to train a small-scale HCNN.



		AF3	FP1	FPZ	FP2	AF4		
F7	F5	F3	F1	FZ	F2	F4	F6	F8
FT7	FC5	FC3	FC1	FCZ	FC2	FC4	FC6	FT8
T7	C5	C3	C1	CZ	C2	C4	C6	T8
TP7	CP5	CP3	CP1	CPZ	CP2	CP4	CP6	TP8
P7	P5	P3	P1	PZ	P2	P4	P6	P8
	PO7	PO5	PO3	POZ	PO4	PO6	PO8	
		CB1	O1	OZ	O2	CB2		

Fig. 1. The organization of DE map. Left: the 62-channel EEG placement in this experiment. Right: the placement is approximately expressed as a map, and each 'pixel' corresponds to a certain electrode. Through this method, the spatial relationship of electrodes are taken into consideration. (F: Frontal, T: Temporal, C: Central, P: Parietal, O: Occipital, Z: Midline).

2.3 HCNN

Here we consider a four-layer HCNN, which consists of two convolution layers and two pooling layers. The layer number is quite limited because the input map size is rather small, and if extra layers are introduced, after more convolution and pooling operations, the two-dimensional character of maps will vanish.

Consequently, the network parameters (e.g. the network depth, the number of feature maps in each layer and the kernel number for each layer) should be carefully appointed to fit different input size and various training goals. From layer to layer, the features becomes increasingly global and abstract, which is similar with the way the human visual cortex works (especially the primary visual cortex in the ventral pathway). The sigmoid function and the pooling operation also endow the network with nonlinear feature-extraction ability, which is vital in accomplishing complex visual goals. The HCNN structure used in this paper is shown in Fig. 2.

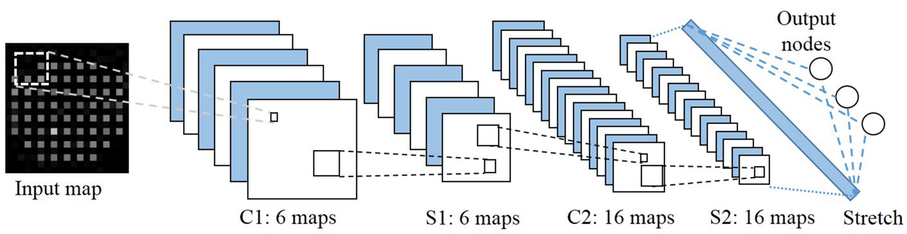


Fig. 2. The HCNN structure. The input map is 20*20. C1 is a convolution layer: the kernel size is 5, and the step is 1, then 6 16*16 maps are formed. S1 is a maxpooling layer, and the scale size is 2, so 6 8*8 maps are obtained. C2 is the second convolution layer: the kernel size is 3, and step is 1, then 16 6*6 maps are formed. S2 is another maxpooling layer, and scale size is also 2, so 16 3*3 maps are obtained here. All maps in S2 are stretched and concatenated to generate a 144-D vector according to their spatial positions. Finally, the vector is fully-connected to 3 output nodes, in which each node corresponds to a certain kind of emotion state: positive, negative and neutral. The activate function is sigmoid.

3 Experiments and Results

3.1 Stimulus

There are four healthy male subjects, and they watch 15 movie slices cut from six emotion-related movies. Each slice is about four minutes long (~240 seconds). During the movie-watching process, 62-channel EEG signals are collected simultaneously [5]. The movie list is shown in Tab 1. The selected 15 movie slices include five positive ones, five negative ones, and five neutral ones. For each subject, the 15 slices are displayed according to the order shown in Fig. 3, which also shows the duration of each slice. The experiment lasts 3394s in total. Then the experiment is repeated three times to compensate for the influence of time, as well as to increase the data amount. The duration between adjacent experiments is about one week. Therefore, for one subject on one frequency band, we acquire 10182 labeled samples. Self-assessment is done during the experiment to eliminate the influence irrelevant factors [16].

The dataset was originally contributed by Baoliang Lu et al. For more detailed information about the data [5] or download it for scientific research use, please log on to the website (http://bcmi.sjtu.edu.cn/~seed/index.html).

Table 1. The movie list.

Movie slices sources	Label
Tangshan Earthquake	Negative
1942	Negative
Lost in Thailand	Positive
Flirting Scholar	Positive
Just Another Pandora's Box	Positive
World Heritage in China	Neutral

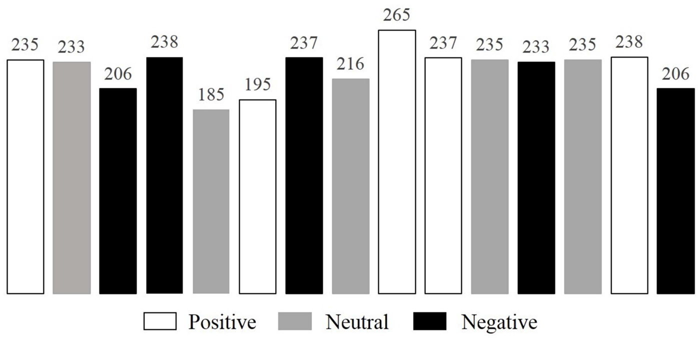


Fig. 3. The slice order (from left to right) and duration (in second).

3.2 Train HCNN

The training process is shown in Fig. 4. The subject is invited to watch movie slices to evoke the electric potential signals that are related to emotion activity. At the same time, EEG signals are recorded on 62 channels. The recorded signals then go to the preprocessing module. The raw EEG data (1000 Hz) is downsampled to 200 Hz sampling rate, and in order to filter the noise and remove the artifacts, the EEG data is processed with a bandpass filter between 0.3 Hz to 50 Hz. Therefore, the high frequency noise is excluded, but the five frequency bands we are interested are maintained. After preprocessing, the EEG signals are ready to provide features.

The feature-extraction and organization operation plays the key role in the present experiment, and it is described as follows: primarily, the signals are divided into multiple 1-s segments according to their durations (we assume that the signal is approximately a stationary process in such short time interval), and in every segment, 256-point STFT with nonoverlapped Hanning window is performed, DE is then calculated on each of the five frequency bands. Secondly, for each frequency band, we organize the DE features as two-dimensional maps according to the method described in Fig.1. We also introduce sparsity by adding all-zero rows and columns to the DE maps, which is good for HCNN training. Finally, the sparse maps of one frequency band, together with the movie-slice labels, are used as the teacher signals to train a HCNN in full-supervised learning algorithm. At the end of this stage, five HCNNs are trained, each one is special for one frequency band. The emotion-related patterns might hide in each of the five frequency bands, but the discriminative capacity is different. We will examine the performance of the five classifiers and find the most efficient bands for emotion recognition.

For each subject on each of the frequency band, 10182 labeled samples are collected. We use 75% (~74000) of the samples to train the HCNN, and the remaining 25% (~2800) are for test (the test samples are not included in the training samples). The initial values of the networks are randomly-appointed. The learning rates are all set to 1, the batch size is 50, and the learning epoch is 600. All the experiments are done in MATLAB (R2014a) software.

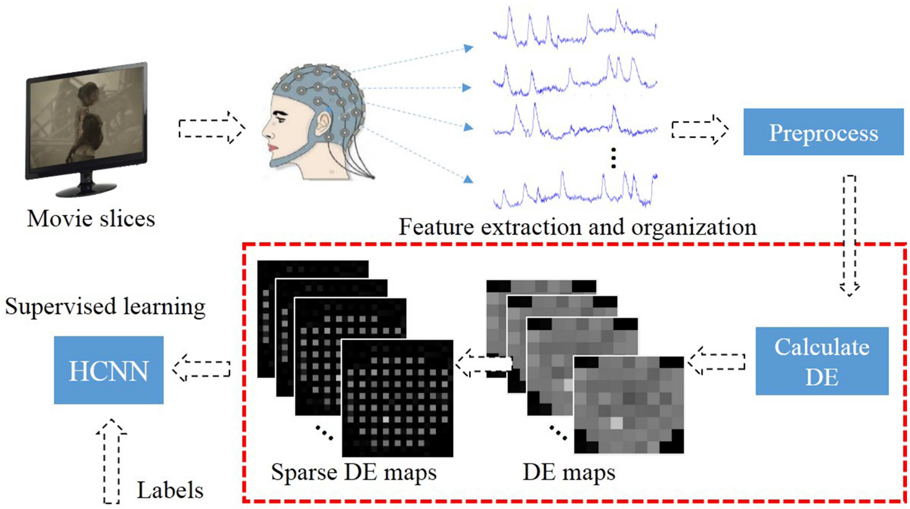


Fig. 4. The training process.

3.3 Train SAE and shallow classifiers

In order to see the different performance of other classifiers, we also implement the emotion classifiers with other models, i.e. the shallow models kernel-SVM, KNN and one-dimensional deep model SAE.

For kernel-SVM, the penalty factor c and the parameter g are determined by grid search (the searching regions are all from 2^{-8} to 2^{8}) and three-fold cross validation. The kernel is RBF (Radial Basis Function). SVM algorithm is efficient in applications where the sample amount is small and the computing capacity is limited.

For KNN, we choose five nearest neighbors to determine the predicted label of each test sample. The distance is simply defined as Euclidean distance. The memory-based KNN algorithm is simple, but the computation burden is relatively heavy.

SAE is the cascade-connected architecture of several Autoencoders (AE). AE is capable of learning the compressed representation of data, and thus widely used for dimensionality-reduction and deep network pre-training (kind of greedy algorithm). The input layer is composed by 400 neurons. The second layer is a hidden layer, where 200 neurons are assigned. The third layer is also a hidden layer, where 100 neurons are assigned. The last layer is the output layer with three neurons, and each neuron corresponds to one kind of emotion state.

We also investigate the consistency of emotion-related electric responses among different peoples. Here we define three HCNN training strategies.

A. Train and test HCNN on data acquired from one same subject (shown in Fig. 4).
B. Train the HCNN on the data acquired from three other subjects, and then test HCNN on a new subject.
C. Pre-train the HCNN on the data of three other subjects, and fine-tune it by the data of a new subject, and then test the HCNN on the new subject.

3.4 Results

Before showing the classification performance, we plan to illustrate the complexity of the previous task. We introduce Adjusted Cosine Similarity (ACS) as criterion to measure the similarity of features for three emotion states. ACS computes the cosine value of two sets of spatial vector, and the bigger the value is, the smaller the angel is, so the more confidence we acquire to assert that the two vectors are the same. Different from traditional cosine similarity (who simply compare similarity on the basis of spatial angel), ACS also take numerical magnitude into consideration. It not only measures similarity in direction sense, but also reflects the magnitude of feature vectors. We computed the mean ACS for each pair of the three kinds of emotion-states on wave band Beta and Gamma, and the spatial angles (radian measure) are summarized in Fig. 5. The angels are all very close to zero, and features belong to different emotion states are much alike.

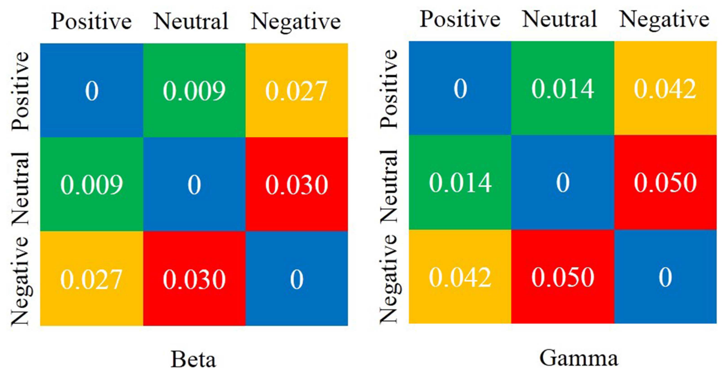


Fig. 5. The mean spatial angels for each pair of emotion-states (on Beta and Gamma).

The performance comparison of the four classifier implementations is summarized in Tab. 2. The results are shown in the form ‘mean (SD)’ (four subjects considered). No matter what kind of classifier is applied, the Beta wave and Gamma wave possess absolute advantage over the others. Also, HCNN and SAE are far better than SVM and KNN. The peak accuracies of Beta-classifier and Gamma-classifier is highlighted in capital. On Beta, the performance of HCNN is around 86%, which exceeds the performance of SAE remarkably. On Gamma, the accuracy obtained by HCNN is around 88%, which beats KNN by a margin of 10%, and much better than SVM, yet the advantage over SAE is not remarkable.

We apply t-test to examine (α=0.05) whether the performance of HCNN is better than SVM, KNN and SAE. The null hypothesis is ‘the performance is different’, and if p-value is bigger than α, the null hypothesis is accepted (on band Beta, HCNN with SVM: p=0.347; HCNN with KNN: p=0.126; HCNN with SAE: p=0.337. On band Gamma, HCNN with SVM: p=0.059; HCNN with KNN: p=0.059; HCNN with SAE: p=0.556).

The performance of HCNNs trained according to different strategies are summarized in Tab. 3. ‘Train’ refers to the accuracy on the training cases, and ‘Test’ refers to the accuracy obtained on the test samples. A, B, C are training strategies defined in 3.3. According to the results, if HCNN trained on other peoples is used directly on a new subject, the accuracy generally shows a downward cliff. On Beta, it is a surprising 50% decline, and on Gamma, a 30% decline occurs. When fine-tune method is applied on networks generated by B, the accuracy of Beta-classifier improves about 30%, but still much lower than that of the strategy A. The performance of Gamma-classifier under strategy A wins C by 8%. The superiority of strategy A over B and C is so obvious that hypothesis testing is not a necessary.

Table 2. The performance of SVM, KNN, SAE and HCNN on five frequency bands.

Classifier	Wave band				
	Delta	Theta	Alpha	Beta	Gamma
SVM	0.597 (0.062)	0.501 (0.033)	0.595 (0.155)	0.732 (0.178)	0.744 (0.097)
KNN	0.533 (0.063)	0.429 (0.056)	0.587 (0.046)	0.697 (0.160)	0.755 (0.090)
SAE	0.491 (0.112)	0.407 (0.090)	0.671 (0.118)	0.783 (0.132)	0.854 (0.081)
HCNN	0.369 (0.032)	0.278 (0.106)	0.390 (0.091)	**0.862 (0.066)**	**0.882 (0.035)**

Table 3. The impact of HCNN training strategy on five frequency bands.

Wave band		Training strategy		
		A	B	C
Delta	Train	0.732 (0.040)	0.759 (0.013)	0.799 (0.042)
	Test	0.369 (0.032)	0.363 (0.023)	0.392 (0.031)
Theta	Train	0.726 (0.031)	0.759 (0.040)	0.741 (0.029)
	Test	0.278 (0.106)	0.421 (0.071)	0.449 (0.028)
Alpha	Train	0.767 (0.061)	0.773 (0.028)	0.849 (0.091)
	Test	0.390 (0.091)	0.344 (0.032)	0.372 (0.066)
Beta	Train	0.969 (0.017)	0.876 (0.036)	0.921 (0.028)
	Test	**0.862 (0.066)**	0.370 (0.019)	0.673 (0.076)
Gamma	Train	0.985 (0.017)	0.966 (0.037)	0.977 (0.036)
	Test	**0.882 (0.035)**	0.498 (0.117)	0.801 (0.096)

4 Discussion and Conclusion

The performance of HCNN classifier is better than SAE, which might be partly attributed to the way we organize the DE features. The two-dimensional maps contains extra spatial information for emotion recognition, and thus good for classifier training. Despite the training process demands more computational ability, HCNN is still a favorable tool to implement EEG-based emotion recognition system.

Deep models (HCNN and SAE) are better than the shallow models. HCNN is suitable, because the layer-wise convolution operations is efficient in feature synthesis and denoising. SAE is favorable, in that the representational ability acquired through goal-driven Back Propagation (BP) algorithm is strong. In this task, DL overbeats shallow models obviously. This phenomenon again shows the advantage of DL algorithm in complex data miming applications (when we evaluate the similarity of EEG features for different emotion states, we find it hard to discriminate them). The advantage of DL primarily lies in the powerful representational ability, which keeps growing as the models go deeper (quite similar to the human brain's working principle). Thus DL owns an insight into the data's internal features hidden deep in nonlinearity.

The results also demonstrate that 'complete transfer' method is not appropriate in EEG emotion recognition tasks, which means that the priori knowledge (now in the form of HCNN initial weights) learned from other peoples is not very useful to the present person. The initial weights learned on other peoples does not help the present HCNN converge faster, but on the contrary, their contribution cannot even match the random-assign method. This also tells us that the difference of EEG response patterns among different persons on the same task is huge, and the emotion-related BCI system for a certain customer should be individually designed to specially endow it with his (her) personal characteristics. However, previous studies [5] showed that for one single person, his (her) emotion-related EEG signal does not change much over time (at least for weeks), so the individually-designed HCNN emotion-reading system does not need frequent updates.

No matter how the features are organized and what kind of classifiers are applied, the frequency bands Beta and Gamma are always the best predictors of the emotion state. As a comparison, the accuracy obtained by the other bands of classifiers are poor and unstable. Such results further reveal the significance of high-frequency brain waves in task-evoked emotion-processing process. Our findings prove that Beta wave and Gamma wave are highly-involved in the reasoning and thinking activities of the brain. Therefore, we should focus on these two bands in the investigation of emotion. Simultaneously, the two bands are good basis for researchers to design more reliable emotion-related BCI systems.

In this paper, we analyze the EEG signal in the frequency domain, yet for each channel, the signal is a time series, which implies that autoregression and joint-regression relationship (between channels) should not be neglected. Therefore, for a further plan, we will introduce Recurrent Neural Networks (RNN), as well as Long-short Time Memory (LSTM) to the present study to conduct a more challenging time-frequency domain research concerning human's emotion.

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