A Frequency Boosting Method for Motor Imagery EEG Classification in BCI-FES Rehabilitation Training System

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Abstract. Common Spatial Pattern (CSP) and Support Vector Machine (SVM) are usually adopted for feature extraction and classification of two-class motor imagery. However, in a motor imagery based BCI-FES rehabilitation system, stroke patients usually are not able to conduct correct motor imagery like healthy people due to the injury of motor cortex. Therefore, motor imagery EEG of stroke patients lacks of specific discriminant features as appearances of healthy people, which significantly blocks CSP to seek the optimal projection subspace. In this paper, a method, which filters EEG into a variety of bands and improves performance through boosting principle based on a set of weak CSP-SVM classifiers, was proposed to solve the problem mentioned above and was evaluated on the EEG datasets of three stroke subjects. The proposed method outperformed the traditional CSP-SVM method in terms of classification accuracy. From data analysis, we observed that optimal spectral band for classification had been changing along with rehabilitation training, which may reveal mechanisms that dominant frequency band may be changed along with rehabilitation training and spectral power distribution may be changed in different stages of rehabilitation. In addition, this work also demonstrated the feasibility of our SJTU-BCMI BCI-FES rehabilitation training system.

Keywords: EEG, Stroke, BCI-FES Rehabilitation System, Frequency Boosting, Common Spatial Pattern, Support Vector Machine.

1 Introduction

Motor imagery based BCI-FES system is a very promising mean for rehabilitation training of strokes[1], which provides an effective training way for patients to link active motor imagery to movements of paralyzed limbs. Functional Electrical Stimulation (FES) is given to patients according to their corresponding motor imagery during training, helping patients learn external limbs controlling through simulating normal limb controlling process of heathy people[2][3].

C. Guo, Z.-G. Hou, and Z. Zeng (Eds.): ISNN 2013, Part II, LNCS 7952, pp. 284–291, 2013.

Common Spatial Pattern (CSP)is one of the most successful approaches in feature extraction of motor imagery EEG[4]. But it cannot seek the optional projection subspace when applied to stroke patients' data due to contamination of strong noise caused by irregular patterns or wrong imagery which are frequently found in the motor imagery EEG of stoke patients. In order to solve the problem, our proposed method incorporates boosting principle which is quite an effective method in dealing with series of weak learners[5]. It can improve classification performance by combining base weak classifiers, even each of them only has a performance that is slightly better than random.From data analysis, we observed that optimal spectral band for classification had been changing along with rehabilitation training, which may reveal mechanisms that dominant frequency band may be changed along with rehabilitation training and spectral power distribution may be changed in different staged of rehabilitation.

The rest of paper was organized as follows: SJTU-BCMI BCI-FES rehabilitation training system was firstly introduced in Section 2. We present the details of the frequency boosting approach in Section 3. A comparative results are given when applying our method and traditional CSP-SVM on the dataset of stroke subjects in Section 4.

2 Methodology

2.1 BCI-FES Rehabilitation Training System

Fig. 1 shows the framework of our multi-Neurofeedback BCI-FES Motor Function Rehabilitation System including data acquisition module, data server module, model training module[6][7], online classification module, online data visualization module[8] and multi-Neurofeedback module.

Raw data is recorded by 16 channels gtec EEG system with a sample rate 256Hz, among which we select medial frontal cortex and earlobe which are used as ground and reference respectively. We can adopt a variety of EEG classifiers in our framework. During our experiment, we used CSP-SVM as online classifier. EEG signals after removing artifacts are then filtered into specific subband such as 8-30Hz, detrended and converted into a format $time \times channel \times window$. CSP will be applied to calculate the optimal projection subspace. However, we noticed that the accuracy of CSP-SVM is not satisfactory. So we proposed a new algorithm described in Setion 3 to improve the performance. In our experiment each window (see details in subsection 2.2) of EEG is transformed into a 4-dimensional feature spaces which fed to SVM.

2.2 Experiment Setting

In general, the subject is required to take part in our experiment cycle 3 times per week, which consists of 3 phases: prior-training for model preparations, multi-Neurofeedback BCI task for rehabilitation and post-training for assessment. All experiments are monitored by a video camera to build tagged videos for further analysis.

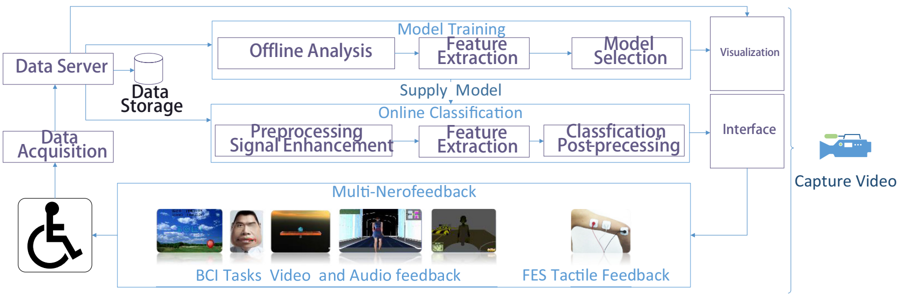


Fig. 1. The framework of multi-Neurofeedback BCI-FES Motor Function Rehabilitation System. BCI Tasks are a series of motor imagery based games giving both video and audio feedback to subjects. The whole system gives a close loop feedback to subject helping them reestablish their motor functional from stoke.

In the prior-training process, a different number of sessions ranged from 5 to 8 will be given to the subject. There are 5 minutes for subjects to relax themselves between sessions. Each session contains 15-16 trials lasting 4 seconds and balances the number of left and right motor imagery tasks. At the beginning of each trial, a bold arrow and a vocal message are given to guide subjects to concentrate on imagining movements of their corresponding part of arms. The time sequence of each trial are cut into 25 sliding windows with width of 1s and step length of 0.125s[6] for online classification. There is a 2-second interval between trials in order to help subjects adjust their mental state to avoid fatigues. The data collection of previous session is used to update model offline, and then it is used for classifying following session data online.

After the prior-training, subjects are asked to finish one or two motor imagery based games such as lifting balloons which appear at the left or right of screen randomly, balancing a ball on a beam and so on. FES is triggered and is used for stimulating one side of subjects' muscles corresponding to current motor imagery, which results in a real movement of their hands or arms. The imagination-stimulation process reconstructs the neuron feed loop between paralysed limbs and corresponding pathological brain cortex of the subject, which takes effects in the rehabilitation treatment[9]. At the end of experiment cycle, a post-training section, two sessions and 16 trials in one session, is conducted to evaluate rehabilitation efficacy.

3 Algorithm Design

CSP cannot seek the right projection subspace when EEG signals are contaminated by strong noise. This is common phenomenon while EEG signals are collected from stroke patients. Recent studies show that the brain functional compensation of damaged brain tissue may be replaced by other part. Supposing this change in spatial may cause the frequency of EEG data changed in some patterns, we try to filter the pre-processed EEG signals into a specific band which may reduce the impact of noisy and classify with SVM to produce a weak learner. Using the framework of Adaboost, we boost each weak SVM learner result by α_m to produce a form of committee whose performance will be better than any of the base classifiers. α_m is give following equation

$$\alpha_m = \ln \frac{BestAccuracy_m}{1 - BestAccuracy_m + \epsilon}. \tag{1}$$

Where $BestAccuracy_m$ is the accuracy for optimal model in round m during iteration. ϵ is to avoid infinity causing by a high accuracy around 100%.

Algorithm 1 described a boost model for two-class classification problem with data from stoke patients. A predefine $BandSet$ contains N bands which use to build model. data is also pre-filtered by band from $BandSet[n]$, detrended and splitted window into $BandWindows_1[n]$ in order to fasten our algorithm. Note that there is square root $\sqrt{\exp a_m}$ which is designed for controlling the boosting speed of incorrect classification data. $DupNum(k)$ is the number of copies for incorrect classification data k during boosting.

Algorithm 1. Frequency Boosting Model Training

for m = 1, 2, ..., M **do**
  for n = 1, 2, ..., N **do**
    Sample $\theta * length(BandWindows_m[i])$ data into $Sample[n]$
    Update $ModelSet[n]$ with
      $Band$: $BandSet[n]$
      $SpatialFilter$: the CSP projection matrix on data of $Sample[n]$
      SVM: SVM Model on CSP features from $Sample[n]$ by $SpatialFilter$
    Use $ModelSet[n].SpatialFilter$ to extract features from $BandWindows_1[n]$, classify with $ModelSet[n].SVM$ and calculate $Accuracy[n]$
  end for
  Find optimal model K by $\arg\max_{k \in [1,n]} Accracy[k]$
  Let $BestModel[m] = ModelSet[K]$ and $\alpha_m = \ln \frac{Accuracy[k]}{1-Accuracy[k]+\epsilon}$
  $BandWindows_{m+1} = BandWindows_m$
  for all incorrect classification data k by $BestModel[m]$ in $BandWindows_1[m]$ **do**
    $num_k = \max\left(1, Round\left(DupNum(k) * \left(\sqrt{\exp a_m} - 1\right)\right)\right)$
    for n = 1, 2, ..., N **do**
      $BandWindows_{m+1}[n]$+=[num_k's copies of $data_k$]
    end for
    (We boost this data num_k times more in next iteration for all bands)
  end for
end for

To improve the performance of our algorithm, the band in set should have some overlap and be different in length and range to make weak learners more selective and maximize the coverage. Parameter θ is used to limit the size of training set and make sampling result randomly enough. A larger θ indicates a larger sample set which may decrease the generalization capability of model, while a extreme small θ may harm the stability during iteration.

In two-class classification problem, we use label 1 to indicate which is belonged to one class and label -1 for the other class. Algorithm 2 use the predictions of M CSP-SVM classifiers in different band with weight α_m to predict the label $y(x)$ of data x. $y[m] \in \{1, -1\}$ is the prediction of weak learner m.

Algorithm 2. Frequency Boosting Classification

for all window segment x in test *dataset* **do**
  for m = 1, 2, ..., M **do**
    Let data = Filter x with $BestModel[m].Band$
    Use $ModelSet[m].SpatialFilter$ to extract features from data
    Let $y[m]$ = Classification result by $ModelSet[m].SVM$
  end for
  $y(x) = sign(\sum_{m=1}^{M} \alpha_m y[m])$
end for

4 Result

Eight stroke patients from Zhejiang Taizhou Hospital participated in our study. After two months training, five patients have achieved apparently improvements while no significant improvements for the rest on three patients. We presume that these three subjects may have missed the best rehabilitation period because they suffered stroke more than eight months ago.

The algorithm is applied on the EEG datasets of three patients (out of the five patients that have achieved apparently improvements) for evaluation. The BandSet is shown in Table 1 according to the discussion in Section 3.

Table 1. Frequency Boosting parameters

Band Set (Start Hz and End Hz)	$5-11$	$9-15$	$13-19$	$17-23$	$21-27$	$25-31$	$29-35$
	$5-13$	$9-17$	$13-21$	$17-25$	$21-29$	$25-33$	$29-37$
	$5-15$	$9-19$	$13-23$	$17-27$	$21-31$	$25-35$	$5-17$
	$9-21$	$13-25$	$17-29$	$21-33$	$25-37$		
Parameters	$M: 30$ $\theta: 2/3$ $\epsilon: 0.001$						

We run our algorithm on each pair of training and testing data for three times to obtain an average accuracy. For comparisons, traditional CSP-SVM method is also implemented on the dataset. We use the last session in prior-training section for testing and remaining ones for training. six weeks out of two months (three weeks per month) are chosen and the accuracy of last day in each week

Table 2. Essential information and sliding window classification accuracies

Subject	Age	Sex	Pathogenesis	week					
				1st	2nd	3rd	4th	5th	6th
1	62	female	cortex injury	48%	56%	57%	59%	65%	62%
2	71	male	basal ganglia injury	58%	60%	56%	67%	64%	67%
3	65	female	basal ganglia injury	58%	57%	74%	66%	70%	79%

has been calculated on test data. Table 2 contains the essential information and sliding window classification accuracies of three subjects.

Compared with traditional CSP-SVM method, frequency boosting gives a better accuracy in the most cases (Fig. 2). It's worthy to mention that the whole experiment also provides a powerful evidence of the feasibility of our motor imagery based BCI-FES rehabilitation system.

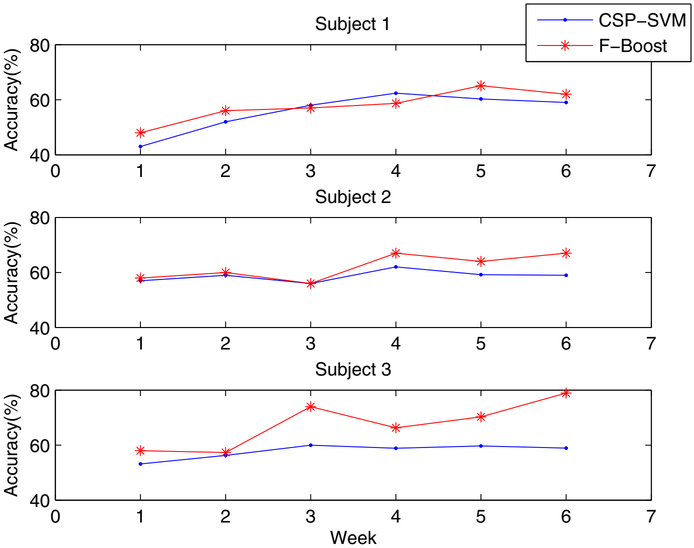
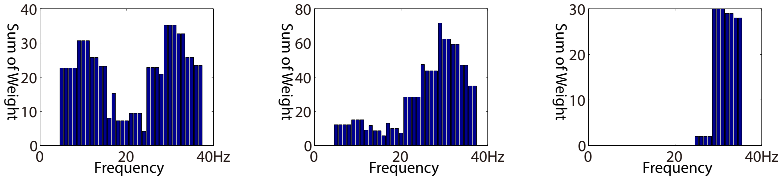


Fig. 2. Comparing between Frequency Boosting and CSP-SVM on test dataset of 3 subjects. Obviously we can find that Frequency Boosting gives a better performance in most cases.

To analyze the frequency changes, we choose the 14th and 57th day to sum up the weight of each optimal weak classification in different frequency as Fig. 3(a) and Fig. 3(b) shown. The importance of gamma-band frequency significantly increased for classification over time.

At the same time we have acquired the motor imagery EEG data of a heathy subject (25age, male), who is an engineer of our rehabilitation system. Apply



(a) 14th day of a subject, beta and gamma band contribute to classifier.

(b) 57th day of a subject, gamma band play a more important role in classifier.

(c) Use gamma band can get a nice classifier for normal subject.

Fig. 3. Comparisons of optimal spectral band for classification

frequency boosting on his EEG signals, a comparison for the weights of each bands is shown as Fig5. 3(c) (use 1 as the weight of each round in this figure). The figure of patients on the 57th day appears a more similar distribution and outline to that of the heathy subject compared with the one at the beginning of rehabilitation. It implies that the frequency of EEG changes along with brain functional compensation and the gamma band (24-37 Hz) make contribution to a high classification accuracy. This may reveal mechanisms that dominant frequency band may be changed along with rehabilitation training and spectral power distribution may be changed in different stages of rehabilitation. Oscillatory activity in the gamma-band range is related to both gestalt perception and to cognitive functions such as attention, learning, and memory[10].

Three other stroke patients were also trained with ordinary medical treatments for two months as a control group which is observed and recorded during the experiment. A much lower clinical rehabilitation parameters of the control group is observed in post assessment, which indicates that our system promotes the rehabilitation of impaired cerebral cortices and accelerates the reconstruction of the neuron feed loop of stroke patients.

5 Summary

In this paper, we proposed an adaptive Adaboost method in frequency for classifying 2-class motor imagery EEG of stroke patients. This method filtered training data with different bands and produced weak CSP-SVM classifiers for following boosted into a better one. Applying both the proposed method and traditional CSP-SVM on the same datasets of stroke subjects, we compared their classification accuracies. The simulation results proved our method outperforms the general CSP-SVM approach. By analyzing the weight of each optimal model, we provide an evidence of the band of EEG frequency changed during rehabilitation, which is also an evidence of feasibility of our BCI-FES rehabilitation system.

A shortcoming of the method is that we didn't have an auto-adapt boundary to control the number of boosting iterations to avoid over-fitting. Considering the accuracy of pervious round and the accuracy gap between suboptimal models in each round, we may improve the performance of current algorithm by given a better weight during boosting. A cross validation for choosing the best model is more convincing than a greedy way for obtaining optimal model.

For future work, we plan to focus on the EEG changes in beta band during rehabilitation to reveal the mechanism. Moreover, we plan to apply our BCI-FES system to more post-stroke cases and collect more data of stroke patients to provide generally evidence the effectiveness of our method or maybe adapt to reach a better performance.

Acknowledgement. The work was supported by the National Natural Science Foundation of China (Grant No. 90920014 and 91120305) and the NSFC-JSPS International Cooperation Program (Grant No. 61111140019).

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