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Gaussian Mixture Modeling in Stroke Patients' Rehabilitation EEG Data Analysis

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***Abstract*— Traditional 2-class Motor Imagery (MI) Electroencephalography (EEG) classification approaches like Common Spatial Pattern (CSP) and Support Vector Machine (SVM) usually underperform when processing stroke patients' rehabilitation EEG which are flooded with unknown irregular patterns. In this paper, the classical CSP-SVM schema is improved and a feature learning method based on Gaussian Mixture Model (GMM) is utilized for depicting patients' imagery EEG distribution features. We apply the proposed modeling program in two different modules of our online BCI-FES rehabilitation platform and achieve a relatively higher discrimination accuracy. Sufficient observations and test cases on patients' MI data sets have been implemented for validating the GMM model. The results also reveal some working mechanisms and recovery appearances of impaired cortex during the rehabilitation training period.**

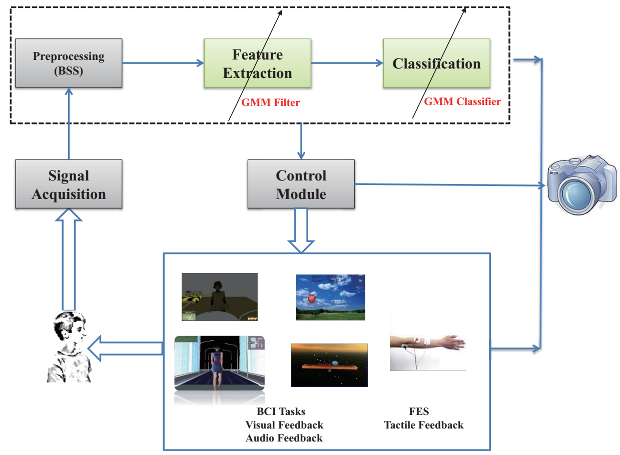

Fig. 1. The framework of our BCI-FES rehabilitation training platform. GMM will be applied on the feature processing module and classification module respectively (marked as green).

I. INTRODUCTION

EEG is the recording of the brain's spontaneous electrical activity over time. 2-class motor imagery (left and right hand motor imagery) EEG studies have been widely undertook in recent years. Accordingly, Brain Computer Interface (BCI) is applied clinically, providing a new criteria for diagnostics of neurological disorders such as stroke[1].

In this study, we propose an active BCI-based motor functional rehabilitation approach to build up a close loop training paradigm. In this approach, 2-class MI based EEG recognition techniques are employed to construct a BCI rehabilitation training platform for stroke patients[2], combined with traditional Functional Electrical Stimulations (FES) therapy as Fig. 1 shows. The system integrates brain activities on Central Nervous System (CNS) induced by customized imagery tasks with FES on corresponding muscles, aiming at helping patients reconstruct the neuroncircuit between paralysis limbs and corresponding pathological brain areas[3].

One of the bottlenecks when implementing MI based BCI-FES rehabilitation system is that conventional methods like common CSP cannot provide a convincing classification accuracy because it may detect a non-optimal orientation for projection under the impacts of irregular imagery patterns[4]. Plenty of adaptive algorithms have been proposed for improvements but they share a common shortcoming that they cannot avoid directly using features which are extracted by CSP with poor discriminant abilities. In this paper, we visualize the original spatial patterns. Based on observations, we build a Gaussian Mixture Model for representing this special kind of mixed features. The model is applied in the preprocessing module as a filter and the classification module as a classifier, respectively. The performance is compared with general CSP-SVM together with an accuracy Upper Bound (UB) reference provided by One Nearest Neighbor (1NN) estimation.

The rest of the paper is organized as follows: Section II provides a brief description about our BCI-FES rehabilitation system and experiment layout. Section III details the schema of Gaussian Mixture Modeling on stroke patients' EEG classification problem. Section IV demonstrates comparative results of GMM at the same time puts forward a novel discovery about the working mechanism of the impaired (stroke) brain cortex.

II. EXPERIMENT FRAMEWORK

Fig. 1 provides a global view of the framework of our BCI-FES training system. FES is integrated in the feedback module that we designed for patients to coordinate the brain activity with imagery tasks (like lifting cups or balancing a beam[5]). Sound notifications and other external prompts have been inserted for improving subjects' concentration during training sessions. Multi-modal interfaces such as camera videos and medical records are reserved for tracking the whole training process.

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A. Parameters and Paradigm

Raw EEG signals are recorded with sample rate 256Hz by the 19-channel g.USBamp amplifier which is connected with 19 electrodes distributed on the EEG cap. After removed artifacts then detrended and filtered, EEG signals are transferred into the classification module. It is worth emphasized that we expand the default alpha and beta band 8-30Hz into 5-40Hz because a recent study provides an evidence that the Event Related Desynchronization (ERD) phenomenon of impaired cortex may cover a wider band in frequency domain than normal parts[6].

Fig. 2 is a sketch of the training paradigm that we customize for training. FES is triggered with a current intensity 20mA in the rehabilitation stage of each subject' daily treatment when they get blocked finishing motor imagery tasks.

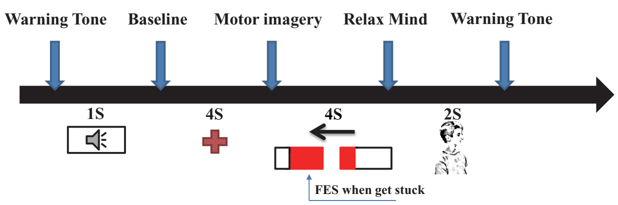

Fig. 2. Rehabilitation training paradigm. FES is triggered when patients get difficulties finishing imagery tasks.

B. Data sets

Seven stroke patients from Zhejiang Taizhou Hospital participate in our study. Table I provides clinical diagnosis data of 10 patients in 8 weeks selected from the 3 months' training, including every week's Fugl-Meyer Motor Assessment (FMA) results for measuring motor function dysfunction[7][8]. The motor imagery EEG of 4 subjects (with "*" after their number in Table I), with a better rehabilitation performance, are chosen as our data set. The data set consists of 8 weeks' EEG data for each subject, from which we randomly select 6-8 sessions per day and 3 days per week. Each session contains 15 numbers of 4-seconds trials with different labeled (left and right) motor imagery and all of the trials are cut into sliding windows with length 1s and step 0.125s. We partition the data into two pieces: everyday's first 5 - 7 sessions of EEG as training set and the last session for testing. The assessment results of a control group with another 3 patients are also provided in the table.

III. Model and Algorithm

A. Common Spatial Pattern

For each segment of EEG data $E(time*channel)$, it is projected onto a subspace by the spatial filter matrix V, which is calculated by CSP as the optimal direction that distinguish two kinds of mental states. Signals with largest eigenvalues maximize the difference of variance of left versus right motor imagery EEG[9]. These signals are the m first and last rows of Z.

$$Z = VE \tag{1}$$

In our experiment, we choose the first and last two eigenvalues ($m = 4$) and after log normalization[10] we get a 4-dimensional feature X for each window segment:

$$X = (x_1, x_2, x_3, x_4) \tag{2}$$

Notice that x_1 and x_4 are generated by the largest and smallest eigenvalues during the transformation, which implies that they have the best discriminant ability among all the four features (relatively).

B. Gaussian Mixture Model Classifier

General methods usually put the feature vector X into a Linear Discriminant Analysis (LDA) or SVM classifier directly and then obtain classification results. As we have mentioned before, noises and inaccurate imagery contents generated by impaired brain regions are difficult to be filtered by classical noise estimation means, which violates the assumptions of CSP that only two different imagery states exist in the space.

The Gaussian Mixture Model are introduced for advanced feature learning. GMM is a probabilistic model based on Gaussian distribution for representing the presence of subpopulations within an overall population[11]. Consider the main components of the left-labeled (or right-labeled) imagery EEG of patients in each dimension of the feature space where X locates:

$$X = \alpha_1 P_1 + \alpha_2 P_2 + e \tag{3}$$

where α_1 and α_2 are linear combination coefficients. The first part P_1 consists of contents that highly fit the outline of accurate left motor imagery, which should be extracted out as the most principal component for supervised classification. These contents scatter around a central point with a gaussian-like distribution theoretically. The second element P_2 is comprised of some weak left motor imagery patterns (a little deviation along the standard direction), high-bandpower noises and wrong (right) imagery. The distribution of P_2 differs in people and imagery sessions. But an assertion is reasonable that P_2 can be decomposed as the following equation represents:

$$P_2 = \sum_{k=1}^{M} \beta_k G_k(\mu, \sigma) \tag{4}$$

where G_k is the $k^{th} (k \geq 0)$ gaussian component of P_2. Notice that most of G could be ignored because they either have a low-power (eg. gaussian noise) or hardly can affect final classification. The rest one e is the permanent tiny Gaussian noises that we need not take into consideration in most cases.

Based on the above analysis, Algorithm 1 and Algorithm 2 illustrate the modeling procedures in detail. In the process, EM algorithm is employed to estimate the combination coefficients and parameters of each gaussian component[12].

TABLE I
FMA ASSESSMENT RESULTS OF 10 SUBJECTS

Subject	Gender	Age	Group	Mean value of each week							
				1st	2nd	3rd	4th	5th	6th	7th	8th
1*	Male	74	Experiment group	22.00	22.00	22.00	23.00	24.00	26.00	26.00	26.00
2*	Female	65	Experiment group	16.00	16.00	18.00	19.00	34.00	34.00	40.00	42.00
3	Male	71	Experiment group	16.00	16.00	16.00	18.00	18.00	18.00	18.00	20.00
4	Male	65	Experiment group	11.00	11.00	11.00	12.00	12.00	14.00	14.00	16.00
5*	Male	67	Experiment group	9.00	12.00	16.00	34.00	34.00	36.00	38.00	40.00
6	Male	60	Experiment group	9.00	9.00	9.00	9.00	10.00	10.00	10.00	10.00
7*	Female	62	Experiment group	12.00	18.00	20.00	20.00	22.00	26.00	26.00	30.00
8	Male	77	Control group	12.00	12.00	12.00	12.00	12.00	14.00	14.00	14.00
9	Male	64	Control group	14.00	14.00	14.00	15.00	16.00	16.00	16.00	16.00
10	Female	62	Control group	16.00	16.00	18.00	18.00	20.00	20.00	22.00	24.00

It should be highlighted that Algorithm 2 directly uses GMM as a classifier and deduce the classification result of test sets by comparing two output probabilities.

Algorithm 1 GMM modeling in CSP feature space

Modeling

Apply general CSP on the training data sets subject-independently and get the optimal projection matrix V and training features $X(dimension * window)$;
Split X into two parts: left-labeled features X_L and right-labeled ones X_R;
Determine essential modeling parameters:
k - maximum number of Gaussian components allowed;
d - the dimension of the feature space;
for Each half part of training feature: $X_p(p \in \{L, R\})$ **do**
  for $i = 1 \to d$ **do**
    Initialize EM parameters with k and the iteration time N, and then begin EM iterations;
    Get the EM output and construct the mixture model M_p^i in the i^{th} dimension of space for m-labeled data.
  end for
end for
Finally we get total $2d$ number of gaussian mixture models for the training data sets.

Here c_i in Algorithm 2 are assigned with a average value $1/d$ for simplicity, and the first and fourth feature (x_1 and x_4, $d = 2$) which have the best discriminant ability are selected as our GMM fitting dimensions. For consistency, we unify $M = 1$ (in Equation 4) in our experiment so that the number of allowed gaussian components is fixed to 2, ignoring residual gaussian noises. Observations in Section IV also verify that 2 gaussian components are adequate to reflect the distribution behaviors of most stroke patients' imagery EEG in each dimension of the feature space.

Another issue needed to be pointed out is that we choose to train $2d$ number of models in every dimension of feature space and then combine them with linear coefficients instead of directly constructing the left and right mixture model in a d-dimensional space. Through priori observations and attempts on the patients' EEG data, we find that in a high-dimensional space the features concentrated around a certain point which locates at the periphery (like dimension curse[13]). The covariance matrix estimated by EM are very sparse and difficult to handle with.

Algorithm 2 Classification algorithm based on GMM

Classification

Extract CSP features T of test data sets by using the projection matrix V in Algorithm 1;
for Each observation t in T **do**
  for $i = 1 \to d$ **do**
    Put the i^{th} dimension of t into mixture models M_L^i and M_R^i and get the output probability P_L^i and P_R^i;
  end for
  Combinations: the probability that t belongs to left: $P_L = \sum_{i=1}^{d} c_i * P_L^i$, the probability that t belongs to right: $P_R = \sum_{i=1}^{d} c_i * P_R^i$, where c_i are the combination coefficients with the constraint $\sum_i^d c_i = 1$;
  Comparisons: if($P_L \geq P_R$ and $P_L \geq \theta$), set the label of t = left; else if($P_R \geq P_L$ and $P_R \geq \theta$), set the label of t = right; else regard t as a noisy observation, where θ is the rejection threshold.
end for

Actually Gaussian Mixture Modeling based on CSP features is a kind of feature learning methods. The above two algorithms describe how to use GMM as a classifier. Another scheme we have attempted is to insert GMM into feature processing procedure to filter out the noisy part of patients' imagery data by the supervising of its output probabilities, and then train a more accurate SVM for classification[14]. We will not demonstrate details due to limited space but we list the comparative results of two implementations in Section IV.

IV. Result and Mechanism

A. Classification Results

The proposed modeling algorithm is evaluated as classification module in our BCI-FES system. Another scenario we mentioned in Section III is also applied on the feature processing module of the system separately. For reference, 1-NN error rate bound is carried out on the test data sets[13]. Mean accuracies of the 4 subjects in 8 weeks are computed

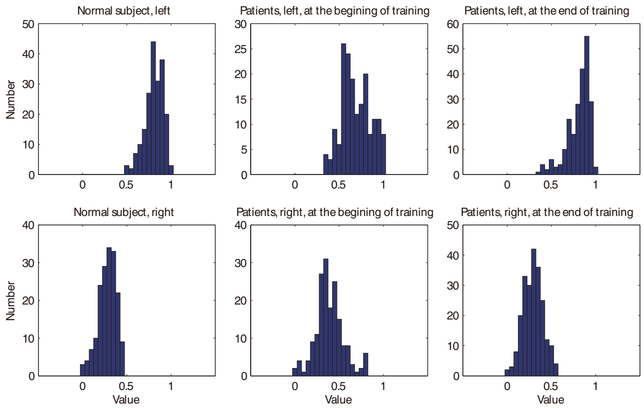

Fig. 3. The distribution histogram of feature x_1 after normalization, including 2-class motor imagery EEG of a normal subject and a patient in different periods.

and listed in Table II. Experiment results indicate that GMM based methods stand out in accuracy. It outperforms CSP-SVM and achieves a high accuracy 77% on subject 2.

TABLE II

MEAN SLIDING WINDOW ACCURACIES (%) OF THE 4 SUBJECTS CALCULATED BY USING DIFFERENT METHODS

Subject	CSP-SVM	GMM Classifier	GMM Filter	UB
Subject 1	46.39	60.80	58.46	76.48
Subject 2	66.05	77.50	73.12	85.70
Subject 5	63.00	74.73	69.30	81.42
Subject 7	57.04	63.48	65.26	78.21
Mean	58.12	69.13	66.61	—-

B. Observations and Mechanisms

Fig. 3 provides a directviewing distribution profile of the CSP feature in dimension x_1. We normalize original features into $(0, 1)$ in each dimension dividedly and then compute a mean value for demonstration, which will not change the relative locations.

It's obvious that the patterns of normal subjects locates separately at the two half of the interval, gathering around two highest center, appearing with a gaussian outline. While the 2-class EEG features of patients share an overlapping area in the surroundings of the boundary (middle 2 sub-figures). Moreover, we observe more than one local maximum centers in patients' EEG in the middle part of Fig. 3, which provides a proof about our assumptions that multi mixture gaussian components exist. The right part of Fig. 3 displays the normalized features of the same patient at the last stage of rehabilitation training (the 8th week). An evident change is observed that the length of overlapping parts between left and right becomes shorter than before. In addition, the secondary local peaks attenuate and gradually approaches the primary center in location. A reasonable surmise about the change is that secondary gaussian components are generated by impaired cortex during imagery and this kind of patterns becomes weak, similar with primary patterns and evanesce at last along with the recovery period gradually.

V. CONCLUSIONS

In this paper, we propose a GMM based feature learning algorithm. The algorithm constructs several mixture models in the subspace of CSP features and produce a probabilistic model for classifying stroke patients' EEG. We have performed a three-month clinical experiment and validated the approach on the data sets we collected in Zhejiang Taizhou Hospital.

A shortcoming of the model is that we have not implemented an auto-adapted algorithm to determine the combination parameters c_i. We also lack some specific methods to exploit effective information from observations that are rejected by the threshold. For future work, boosting will be introduced to learn and regulate the combination weights in Algorithm 2. Kernel methods are also taken into considerations for mapping CSP features into a kernel space so that we can construct higher-dimension gaussian components for better describing the distribution of patients' imagery patterns.

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