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Classification of Three Class Hand Imagery Movement with the Application of 2-Stage SVM Model

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Abstract

Classification of multiple motor states of human brain waves will improve the applicable ability to brain – computer interfacing system and neuroprosthesis. In this research, we aim at extending classifier ability to three class imagery movement states including: left hand imagery movement, right hand imagery movement and rest state. We propose to implement new classifier using combination of discriminated features for input feature vector and classifying model based on 2-stage SVM. For the feature vector construction, ANOVA-based feature selection method is proposed to use which resulting in 14% reduction of number of features required for the process. The avarage classification accuracy of our proposed system is achived with 80,75% when evaluated on Physionet dataset. The study demonstrate that proposed IHMv classifier can distinguish more output classes than other researches with less number of electrodes while maintaining similar accuracy classification. Therefore, our system can be applied to BCI system to create controlling commands to peripheral devices or computer application through motor brain waves.

Keywords: EEG, 3 - class imagery hand movement, 2-stage SVM model, Wavelet, motor cortex, ANOVA

1. Introduction

Using EEG signals to characterize motor activities of human brain are of interest of many researchers. Aim at translating recorded motor signals into control command, many researchs has been carried out to classify different motor tasks including both fist and feet [1], finger movement [2]. Hand imagery movement – related EEG signals have been used in many BCI applications and obtained promising classification accuracy [3-6]. Surprisingly, many researches focus on two-class classifiers which mostly for left and right imagery hand movement. A classifier that can distinguish hand imagery movement with rest state that will facilitate practical use of BCI system, is still not mentioned. Besides, to characterize movement –related EEG signals and create input feature vector for classifiers, several methods such as PLV[3], CSP [5],[7], WPICA [8] have used of many electrodes which may increase accuracy of system but also increase preparation time for BCI application and inconvenience for users. In order to extent the applicable of motor – related EEG signals classifiers, we propose a three – class hand imagery classifier including: left hand imagery movement, right hand imagery movement and rest state using machine learning algorithms. Besides, the accuracy performance of the system depend on a combination of discriminate features. In [9], we have presented an extension set of discriminate features using wavelet-based time-frequency feature extraction method. Those features are potential used to create an input feature vector for three – class classification model. Those features are generated from only 2 channel C3, C4 which located over human brain motor area have shown their ability to pick up hand motor information [10],[8]. To remove redundant features for our classification problems, in this study, we also propose ANOVA – based feature selection method through F and p value.

This paper is organized as follows: Section 2 presents the combination of discriminate features for feature vector construction and ANOVA – based feature selection method. Section 3 describes Physionet dataset. Section 4 describes our proposed 2-stage SVM classification model for three –class problem. Last section is results and disscusions.

2. ANOVA – based feature selection for 3 – class hand imagery movement classfication.

Wavelet – based time-frequency domain method has shown the feasibility to create features that contain both time and frequency content of EEG signals [1], [9]. In this method, EEG signals are decomposed into details coefficients that corresponding to different frequency bands. Then, by application of quantitative algorithms to interested detail coefficients, we can create good features that characterize EEG signal. In our previous study, we have proposed potential

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features set to characterize IHMv EEG signals and prove the performance of features in discrimination of three hand imagery movement classes. Feature set generated from EEG signals include: MMAV, SSI, RMS, WL, ZC, SSC, WAMP, Shan_En, Log_En, 3 Hjorths parameters. Candidate features are extracted from C3 and C4 channel in cD3, cD4, cD5 coefficients which are equivalent to theta, beta and alpha EEG band. This result in a 72 dimensional feature vector for each trial (12 features x 3 frequency band x 2 channels) are described details in [9]:

Analysis of variance

ANOVA Analysis of variance is statistical method that can evaluate discrimination among multiple populations of quantitative variable. ANOVA method test the null hypothesis (H_0) that all means (μ_j) of different imagery motor tasks are equal.

H_0: $\mu_{Lf\_IHMv} = \mu_{Ri\_IHMv} = \mu_{Re\_IHMv}$

F ratio which help us to evaluate null hypothesis is defined as:

$$\frac{variation\ among\ sample\ mean}{natural\ variation\ within\ groups} = \frac{MS_B}{MS_W}$$

In which variability within groups is quantified as sum of squares of the differences between each value and its group mean. And variation among groups is quantified as sum of the squares of the differences between the group means and the grand mean (the mean of all values in all groups). We denote fea_{ij} is the feature of i-th IHMv EEG signal and class j

Firstly, we calculate mean sum of squares within the group:

$$MSW = \frac{\sum_j (\overline{n_j} - 1)s_j^2}{(N-k)}$$

And mean squares between the group means is computed as:

$$MSB = \frac{\sum_j n_j(\overline{fea}_j - \overline{fea})^2}{k-1}$$

Where $\overline{x_j}$ is mean of class j samples, $\overline{x}$ is the grand mean of all samples. n_j and s_j is sample size and standard deviation of class j, $N = n_{Lf\_IHMv} + n_{Ri\_IHMv} + n_{Re\_IHMv}$, k is the number of motor imagery class (k = 3)

Anova – based feature selection method

Reducing number of irrelevant features can reduce the running time of the learning algorithms and yields a more general classifier. To remove irrelevant features for input feature vector of motor imagery classifier, we proposed to use ANOVA-based feature selection method.

Resulted F and p value will help us to evaluate the discrimination performance of each individual features among three hand imagery class. In this proposed method, each individual feature will be evaluated independently and is chosen to induce classification models according to the following rule: (1) i-th feature f_i will be calculated by ANOVA to obtain F and p value. (2) Chose feature f_i that have $F > F_{critical}$ with the confident of 95% (p<.05). F critical is the value depend on the specific test dataset that the test statistic must exceed to reject the null hypothesis. (In this case $F_{critical}$ = 3.0014). Evaluate on Physionet database, we selected best 62 features (f_1 - f_{62}) (a 14% reduction of the number of candidate features) extracted from C3 and C4 channel shown in Table 1.

3. Physionet dataset

To evaluate the performance of our classifiers, we used Physionet dataset [11]. This dataset is provided by researchers using and applying BCI2000 framework. We use first 20/109 subjects to create training data. Each subjects have to carry out 2 – minute trials in three sections (R04, R08, R12). In each section, subject implement 3 tasks including:

Table 1. ANOVA – based selected features for three class hand imagery movement classification

	C_3^θ	C_3^α	C_3^β	C_4^θ	C_4^α	C_4^β
RMS	f_1	f_2	f_3	f_4	f_5	f_6
WL	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}
MMAV	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}
SSI	f_{19}	f_{20}	f_{21}	f_{22}	f_{23}	f_{24}
ZC		f_{25}	f_{26}	f_{27}	f_{28}	
SSC	f_{29}	f_{30}	f_{31}	f_{32}	f_{33}	f_{34}
ShanEn	f_{35}	f_{36}	f_{37}	f_{38}	f_{39}	f_{40}
LogEn	f_{41}	f_{42}	f_{43}	f_{44}	f_{45}	f_{46}
WAMP	F_{47}	F_{48}	F_{49}	f_{50}	f_{51}	f_{52}
HjAct	f_{53}	f_{54}	f_{55}	f_{56}	f_{57}	f_{58}
HjMobi	f_{59}	f_{60}		f_{61}	f_{62}	

Trials= {T_1,T_2,T_3}

in which T_1 – Left hand imagery movement,

T_2 – Right hand imagery movement,

T_3 – Rest state.

BCI framework use 64 electrode montage follow international standard 10/20. All data set is sampling at frequency of 160Hz. We pre-processing data channels by zero –phase FIR bandpass of 1-40Hz. To increase SNR, filtered data signal is spatial filtered by large Laplacian spatial filters.

Data normalization

Features value of different subject is normalized by:

$$V_{norm} = \frac{V - \min}{\max - \min}$$

In which V is feature value of each IHMv segment, min and max is the minimum and maximum of feature value of all IHMv of each subject. As the results, all the value are in range of [-1, +1]

4. Classification of 3 IHMv classes based on proposed 2 – stage SVM model

4.1 Built feature vector from combination discrimination feature set

By applying ANOVA – based feature selection method, we proposed to use combination of 62 features as an input vector for classification model. Each feature f_i is arranged in order to create feature vector has dimension 62 x 1. The structure of tranining data include n samples are describe as follow in figure 1:

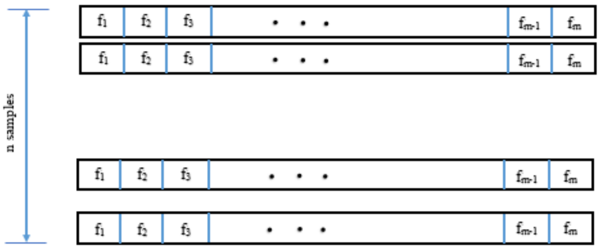

Fig 1. Training dataset

Extract from Physionet dataset, we have training samples size n = 1579 in which 700 Re_IHMv samples, 345 Lf_IHMv samples, 345 Ri_IHMv samples. Each sample is assigned with IHMv tags to support training stage.

4.2 Support vector machine SVM

Support vector machine (SVM) is classification paradigm that have been frequently used in many researches [6][12-13]. In nonlinear SVM model, input data is mapped into high dimension feature space that can be linear separated. SVM model finding the best hyperplane that can separate all data point of one class from those of the other class. Training algorithms SVM is simultaneously maximize classification performance while minimize the possibility of over fitting with specified dataset. We construct classifier by Matlab software with RBF Kernel SVM [14]. To estimate optimum parameter of SVM hyperplane, in this study, we use grid-search and hold-out validation.

4.3 Proposed three – class hand imagery movement classifier based on 2 – stage SVM

Since SVM classifier is for two-class problem, we employed classifiers combination to distinguish three pattern classes. This approach run 2- stage SVM classifiers in a cascade model shown in Figure 2: SVM stage 1 and SVM stage 2. The three output classes include: Left hand imagery movement (Lf_IHMv), right hand imagery movement (Ri_IHMv), rest state (Re_IHMv). The first stage classifier SVM1 is responsible for classifying data into two groups which are: rest groups and imagery movement group (non-Rest IHMv). The second stage classifier simultaneously separate data into two group which are: Left hand imagery movement group and Right hand imagery movement group. The output from 2-stage SVM is determined by combining decisions of these two classifiers as follow in Table 2.

Our model is use supervised learning method for classification in which all training data is supervised and labeling. Input training data is provided by Physionet dataset. Each SVM stage will be trained to create a hyperplane for two class.

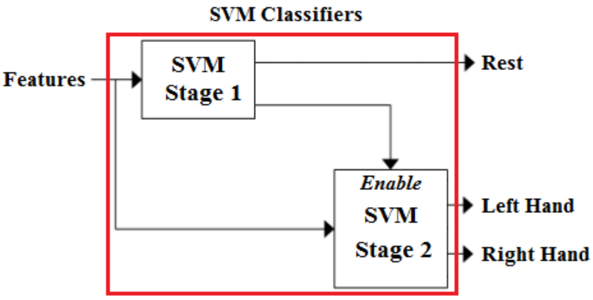

Fig 2. Three class hand imagery movement classification based on 2 –stage nonlinear SVM model

In table 2, left hand imagery movement class Lf_IHMv is marked as 1, right hand imagery movement class Ri_IHMv is marked as -1, and rest state Re_IHMv with the marked as 0.

Table 2 Output determination of classifier

SVM1 (non-rest/rest (Re_IHMv))	SVM 2 (Lf_IHMv/ Ri_IHMv)	Classification result	Output
1	1	1	Left hand
1	-1	-1	Right hand
0	1/-1	0	Rest

6. Results and classification performance of a proposed 3IHMv_SMV2 classifier

Specification of our proposed 3 class IHMv classifier is illustrated in table 3.

Ten models are evaluated from training data with the optimum accuracy of 92%. The average classification accuracy of 3IHMv_SVM2 classifier is 80.75%. Figure 3 presents the average sensitivity (True positive ratio TPR), specification (True negative ratio – TNR) and Area under curve of ROC of each output class corresponding to Lf_IHMv, Ri_IHMv, Re_IHMv. As seen in figure 3, the sensitivity of rest state is highest which is 83,74% while left and right hand imagery is 76,91% and 78,72% respectively. Remember that number of rest samples is almost double comparing to left and right hand imagery samples.

Table 3 Technical specification of our proposed 3IHMv_SVM2 classifier:

Specification	Value
Classification model	SVM
Number of stage	2
Output class	3
Transformation function	RBF Kernel
Input feature vector	ANOVA: 62 features

In the table 4, we compare the classification accuracy of our proposed approach with that of other studies [3],[5],[6] which show an increase of classification rate of 5%. Meanwhile, our proposed classifier have been extent to discriminate three output class compare to others.

Although, the comparison only have relatively meaning as other study use different frameworks in different datasets. By applied in large dataset, our proposed method show a promising classification accuracy for a larger population. The use of many features to characterize EEG signal can possibly increase computation time but still maintain acceptable accuracy classification and reduction of analyzed electrodes.

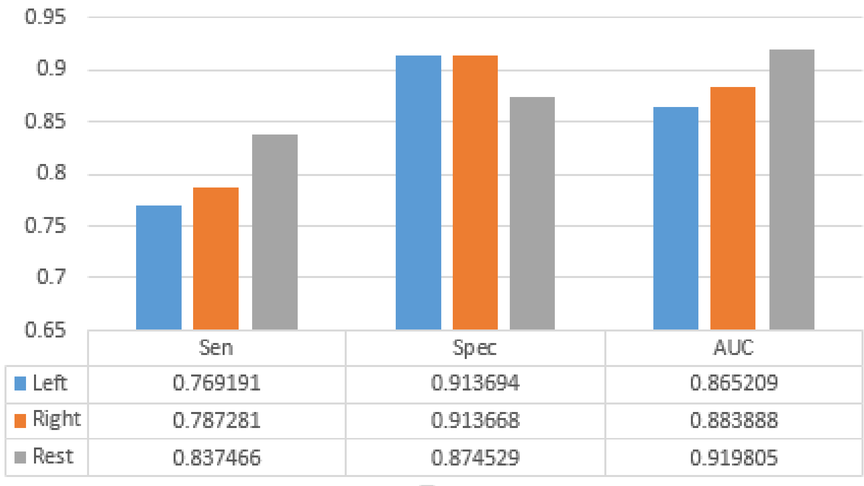

Fig. 3 Classification accuracy of 3IHMv_SVM2.

Table 4. Accuracy performance comparison in discriminate different hand imagery hand movement

	Proposed method	**Cheolsoo Park [6] (2013)**	**Ana Loboda [3] (2014)**	**Goeorge Townsend [5] (2004)**
AvAcc	80,75%	MEMD: 75,6% ±5.2 and NA-MEMD: 78.7±3.7	71,55% (13-30Hz); 65,55% (8-13Hz)	
TPR L, Ri, Re	L: 76,91% Ri: 78,72% Re: 88,74%		L:68%, R:75,1% (beta band), L:60,5% R:70,6% (mu band)	Ri: 69 - 84%, L: 67% - 86%
AUC L, Ri, Re	L: 86,52% Ri: 88,38% Re: 91,98%			Ri: 73 - 92% L: 72 - 93%
Output classes	3	2	2	2

6. Conclusions

To extent the applicable of hand imagery movement EEG signals to BCI, a new hand – imagery movement classifier was proposed in this paper. In which, imagery hand movement EEG signal is characterized by a combination of discriminate features. Aim at reduction of processing EEG channel, only two channel C3, C4 are used in feature extraction method ANOVA based feature selection is proposed to use in order to remove certain irrelevant features for our problem. Final feature selection result is obtained with 14% reduction of the number of features require for feature vector. To extent classification ability of hand imagery movement classifier, our proposed system is constructed with 2 –stage SVM with the output is the combination decisions of the two classify stages. Evaluated on Physionet dataset, a promising classification accuracy of our proposed three class 3IHMv_SVM2 classifier is achieved approximately 80% on average. The average classification sensitivity for left hand was 76,91%, right hand was 78,72% and rest state was 88,74%. The 3 class classifier have shown equivalent accuracy with other 2 – class discriminate methods. The proposed classifier has demonstrate the robustness and easiness in distinguishing imagery left hand movement, imagery right hand movement and rest state.

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References

[1] Mohammad H. Alomari, E. A. (2014). Wavelet-based feature extraction for the analysis of EEG signals associated with imagined fists and feet movements. Computer and Information Science, 7(2), 17-27. doi:10.5539/cis.v7n2p17

[2] C.Vigneshwari, V. S. (2013). Analysis of Finger Movements Using EEG Signal. International Journal of Emerging Technology and Advanced Engineering, 3(1), 583-588

[3] Ana Loboda, A. M. (2014). Discrimination of EEG-Based Motor Imagery Tasks by Means of a Simple Phase Information Method. (IJARAI) International Journal of Advanced Research in Artificial Intelligence, 3(10), 11-15

[4] Tao Wanga, J. D. (2004). Classifying EEG-based motor imagery tasks by means of time–frequency synthesized spatial patterns. Clinical Neurophysiology, 115, 2744–2753.

[5] George Townsend, B. G. (2004). Continuous EEG Classification during Motor Imagery—Simulation of an Asynchronous BCI. IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, 12(2), 258-265

[6] Cheolsoo Park, D. L. (2013). Classification of motor imagery BCI Using Multivariate Empirical Mode Decomposition. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21(1), 10-22.

[7] Xinyang Yu, P. C.-B. (2014). Analysis the effect of PCA for feature reduction in non-stationary EEG based motor imagery of BCI system. Optik, 125, 1498–1502

[8] Zhongxing Zhou, B. W. (2012). Wavelet packet-based independent component analysis for feature extraction from motor imagery EEG of complex movements. Clinical Neurophysiology, 123, 1779–1788

[9] Pham Phúc Ngọc, Vũ Duy Hải, Phạm Văn Bình, Nguyễn Duy Tùng, Vũ Thị Hạnh, Nguyễn Đức Thuận (2015). Developement of features set for classification of imagery hand movement - related EEG signals. Tạp chí Khoa Học & Công Nghệ các Trường Đại học Kỹ thuật. *109.*

[10] Nuri F. Ince, F. G. (2009). Adapting subject specific motor imagery EEG patterns in space–time–frequency

for a brain computer interface. Biomedical Signal Processing and Control, 4, 236–246

[11] Schalk, G. M. (2004). BCI2000: A General-Purpose Brain-Computer Interface (BCI) System. IEEE Transactions on Biomedical Engineering , 51(6), 1034-1043

[12] Saugat Bhattachryya, Amit Konar, D.N Tibarewala (2014). A differential evolution based energy trajectory planner for artificial limb control using motor imagery EEG signal. Biomedical Signal Processing and Control, 11, 107-113.

[13] Mohammad H. Alomari, A. S. (2013). Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning. International Journal of Advanced Computer Science and Applications,, 4(6), 207-212

[14] S.S. Keerthi, C. L. (2003). Asymptotic behavior of support vector machines with Gaussian Kernel. Neural Comput, 15(7), 1667-1689