ANALYSIS OF COMPREHENSIVE STUDY OF MOTOR IMAGERY CLASSIFICATION

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Abstract

The biomedical image and data analysis play an important role for the detection and predication of critical illness and disorder. The major contribution for motor imagery classification is nervous and human brain related control disease. The motor imagery is raw signal form of recorded data of human brain. In this paper analyzed the process of classification and detection of motor imagery related disease detection. The major bottleneck problem is extraction of features of complex structure of recorded signal. The transform-based function impart the impact the correlation for mapping of feature and data space of classification algorithm. The detection and classification process faced a problem of feature selection and mapping of feature component. The various authors proposed neural network and machine learning based classification algorithm.

Keywords: - Motor Imagery, Classification, Neural Network, Wavelet Transform

Introduction

Brain computer interface provides platform for the analysis of human physical and kinetics behaviors analysis. Motor imagery based BCI is a very productive communication method for people with motor disabilities. Motor Imagery (MI) is a mental process wherein the subject imagines that he is performing a specific motor action such as a hand or foot movement without otherwise performing it in reality. Electroencephalogram (EEG) signals are used as inputs to BCI systems. EEG signals are feature extracted in order to overcome the contaminations of noise and artifacts in them. Soft computing algorithms are then used in the classification of different brain patterns obtained upon performing different motor imagery tasks. A BCI system measures brain activity and translates it into control signals. These control signals can be used to construct new augmentative technologies. People with motor disabilities need augmentative technologies corresponding to natural ways of communications. A spatial filter maximizes the variance of spatially filtered signals under one condition, while minimizing it for the other condition. Raw scalp EEG potentials are known to have poor spatial resolution due to volume conduction and smearing effect. If the signal of interest is weak while other sources produce strong signals in the same frequency range, then it is difficult to classify two classes of EEG measurements. The neurophysiological background of the MI based BCIs is that motor activity, both actual and imagined, causes an attenuation or increase of localized neural rhythmic activity called Event-Related Desynchronization (ERD) or Event-Related Synchronization (ERS). The Common-Spatial-Pattern (CSP) algorithm is highly successful in calculating spatial filers for detecting (ERD/ERS)[7-8]. In the rest paper, section II-literature survey, section III: comparative result analysis, section IV-conclusions & future scope.

II. LITERATURE SURVEY

Yu Zhang, Guoxu Zhou, Jing Jin, Qibin Zhao, Xingyu Wang and Andrzej Cichocki Et al. [1] they introduce a sparse Bayesian method by exploiting Laplace priors, namely, SBLaplace, for EEG classification. A sparse discriminant vector is learned with a Laplace prior in a hierarchical fashion under a Bayesian evidence framework. All required model parameters are automatically estimated from training data without the need of CV. Extensive comparisons are carried out between the SBLaplace algorithm and several other competing methods based on two EEG data sets. The experimental results demonstrate that the SBLaplace algorithm achieves better overall performance than the competing algorithms for EEG classification. Leonard J. Trejo, Karla Kubitz, Roman Rosipal, Rebekah L. Kochavi and Leslie D. Montgomery Et al. [2] The development of simpler and more general models, which apply to a broad set of subjects, will require considerable additional research. Another well-known problem in the applied EEG community is that the performance of classification algorithms from day to day, or at different times of day is unstable. Additional research is needed to develop methods for stabilizing the link between EEG features and mental states such as fatigue or alertness over long periods of time. Haider Raza, Hubert Cecotti and Girijesh Prasad Et al. [3] hey evaluate the performance of four methods for frequency band selection applied to binary motor imagery classification: forward-addition (FA), backward-elimination (BE), the intersection and the union of the FA and BE. These methods automatically select and learn the best discriminative sets of frequency bands, and their corresponding CSP features. The performances of the discussed methods are evaluated on binary motor imagery classification using a publicly available real-world dataset.

Jeong-Hwan Lim, Jun-Hak Lee, Han-Jeong Hwang, Dong Hwan Kim, Chang-Hwan Im Et al. [4] They introduced a hybrid mental spelling system which prevents additional typing of BACKSPACE to correct typos. In order to detect typos, simultaneously utilizes both EEG signals recorded from the occipital area and the horizontal eye-gaze direction information extracted from a low-cost webcam-based eye tracker. In their online experiments conducted with 10 healthy participants, at least 16.6 typos could be prevented, from the results, verifying that the discussed strategy could effectively enhance the performance of the SSVEP-based mental spelling system. Laura Acqualagna, Sebastian Bosse, Anne K Porbadnigk, Gabriel Curio, Klaus-Robert Müller, Thomas Wiegand and Benjamin Blankertz Et al. [5] they investigate the correlation of the EEG-based measures with the outcome of the standard behavioral assessment. As stimulus material, they used six gray-level natural images in six levels of degradation that were created by coding the images with the HM10.0 test model of the high efficiency video coding (H.265/MPEG-HEVC) using six different compression rates. The degraded images were presented in rapid alternation with the original images. In this setting, the presence of SSVEPs is a neural marker that objectively indicates the neural processing of the quality changes that are induced by the video coding. Dilshad Begum, K. M. Ravikumar, James. Mathew and Sanjeev Kubakaddi Et al. [6] Recent electrophysiological studies support command-specific changes in the electroencephalography (EEG) that have promoted their intensive application in the noninvasive brain computer interfaces (BCI). They investigate wavelets and adaptive neuro-fuzzy classification algorithms to enhance the classification accuracy of cognitive tasks. Using a standard cognitive EEG dataset, They demonstrate improved performance in the classification accuracy with the discussed system.

James J. S. Norton, Dong Sup Leeb, Jung Woo Leed, Woosik Lee, Ohjin Kwon and Phillip Won Et al. [7] They introduce a soft, foldable collection of electrodes in open, fractal mesh geometries that can mount directly and chronically on the complex surface topology of the auricle and the mastoid, to provide high-fidelity and long-term capture of electroencephalograms in ways that avoid any significant thermal, electrical, or mechanical loading of the skin. Feifei Qi, Yuanqing Li and Wei Wu Et al. [8] a novel algorithm, termed regularized spatio-temporal filtering and classification (RSTFC), for single-trial EEG classification. RSTFC consists of two modules. In the feature extraction module, an l2-regularized algorithm is developed for supervised spatio-temporal filtering of the EEG signals. Unlike the existing supervised spatio-temporal filter optimization algorithms, the developed algorithm can simultaneously optimize spatial and high-order temporal filters in an eigenvalue decomposition framework and thus be implemented highly efficiently. In the classification module, a convex optimization algorithm for sparse Fisher linear discriminant analysis is discussed for simultaneous feature selection and classification of the typically high-dimensional spatio-temporally filtered signals. Minho Kim, Byung Hyung Kim and Sungho Jo Et al. [9] The developed hybrid interface is evaluated through target pointing and selection experiments. Eye movement is interpreted as cursor movement and noninvasive BCI selects a cursor point with two selection confirmation schemes. Using Fitts' law, the discussed interface scheme is compared with other interface schemes such as mouse, eye tracking with dwell time, and eye tracking with keyboard.

Oana Diana Eva and Anca Mihaela Lazar Et al. [10] The purpose of the quantitative research is to compare classifier in order to determinate which of them has highest rates of classification. The power spectral density method is used to evaluate the (de)synchronizations that appear on Mu rhythm. The features extracted from EEG signals are classified using linear discriminant classifier (LDA), quadratic classifier (QDA) and classifier based on Mahalanobis Distance (MD). The differences between LDA, QDA and MD are small, but the superiority of QDA was sustained by analysis of variance (ANOVA). Chi Zhang, Li Tong, Ying Zeng, Jingfang Jiang, Haibing Bu, Bin Yan and Jianxin Li Et al. [11] EThe combination of discrete wavelet transforms and independent component analysis (ICA), wavelet-ICA, was utilized to separate artifact components. The artifact components were then automatically identified using a priori artifact information, which was acquired in advance. Subsequently, signal reconstruction without artifact components was performed to obtain artifact-free signals. The results showed that, using this automatic online artifact removal method, there were statistically significant improvements of the classification accuracies in both two experiments, namely, motor imagery and emotion recognition. Younghak Shin, Seungchan Lee, MinkyuAhn, Hohyun Cho, Sung Chan Jun and Heung-No Lee Et al. [12] they aim to analyze noise robustness of the SRC method to evaluate the capability of the SRC for non-stationary EEG signal classification. For this purpose, they generate noisy test signals by adding a noise source such as random Gaussian and scalp-recorded background noise into the original motor imagery-based EEG signals. Using the noisy test signals and real online-experimental dataset, they compare the classification performance of the SRC and support vector machine (SVM). Furthermore, they analyze the unique classification mechanism of the SRC. They observed that the SRC method provided better classification accuracy and noise robustness compared with the SVM method.

Huijuan Yang, SiavashSakhavi, Kai Keng Ang and Cuntai Guan Et al. [13] they evaluated and analyzed the robustness of the SRC method against the non-stationarity of EEG signal classification. For this purpose, they generated noise corrupted EEG test signals using two noise sources such as random Gaussian noise and scalp recorded background noise.Ye Liu, Qibin Zhao and Liqing Zhang Et al. [14] they usually define frequency bands and channels configuration that related to brain activities beforehand. In this study, a robust tensor-based method is discussed for a multiway discriminative subspace extraction from tensor-represented EEG data, which performs well in motor imagery EEG classification without the prior neurophysiologic knowledge like channels configuration and active frequency bands. Motor imagery EEG patterns in spatial-spectral-temporal domain are detected directly from the multidimensional EEG, which may provide insights to the underlying cortical activity patterns. Extensive experiment comparisons have been performed on a benchmark dataset from the famous BCI competition III as well as self-acquired data from healthy subjects and stroke patients.

III. COMPARATIVE RESULT ANALYSIS

Analysis of EEG classification of data used three methods SVM, MLP and DNN. The methods of classification used the optimal feature selection of different bands of data and raw signal as input for the process of classification. The description of classification result discusses here.

Signal	SVM		MLP		DNN	
	16 DF-Dimension Features	8 DF-Dimension Features	16 DF-Dimension Features	8 DF-Dimension Features	16 DF-Dimension Features	8 DF-Dimension Features
Raw	88	89	90	91	93	94
Delta	86	88	89	90	93	95
Theta	89	91	92	93	95	96
Alpha	85	88	89	90	92	93
Beta	86	89	91	92	94	95

Table 1: Comparative analysis of Accuracy using SVM, MLP and DNNwith 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

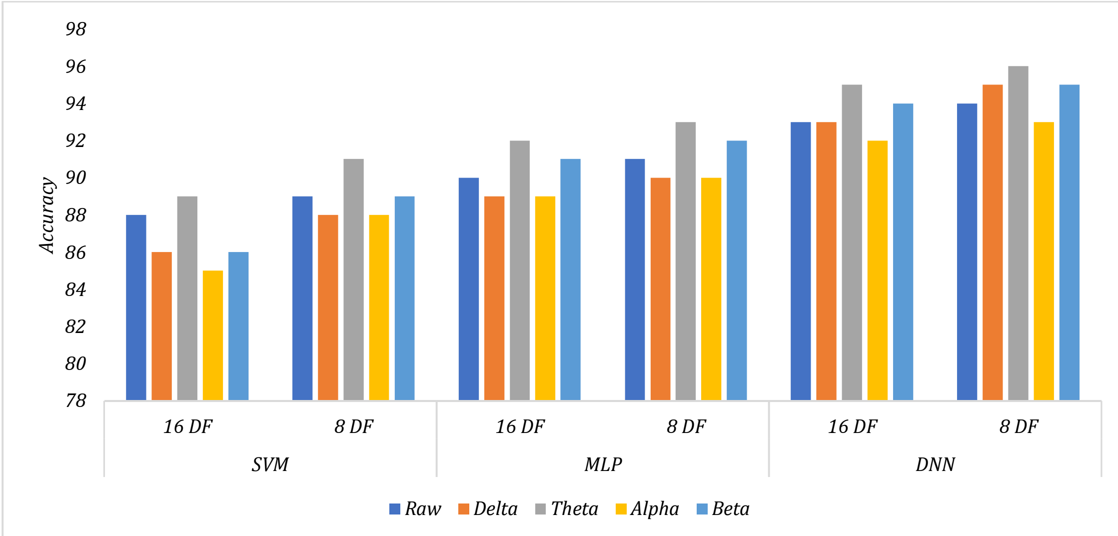

Figure 1: Comparative performance analysis of Accuracy using SVM, MLP and DNN with 16-dimension and 8-dimension features with signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

Signal	SVM		MLP		DNN	
	16 DF-Dimension Features	8 DF-Dimension Features	16 DF-Dimension Features	8 DF-Dimension Features	16 DF-Dimension Features	8 DF-Dimension Features
Raw	75	78	79	82	85	88
Delta	76	79	80	81	84	90
Theta	78	83	84	86	87	92
Alpha	74	80	82	84	85	89
Beta	79	83	85	86	89	92

Table 2: Comparative analysis of Precision using SVM, MLP and DNN with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

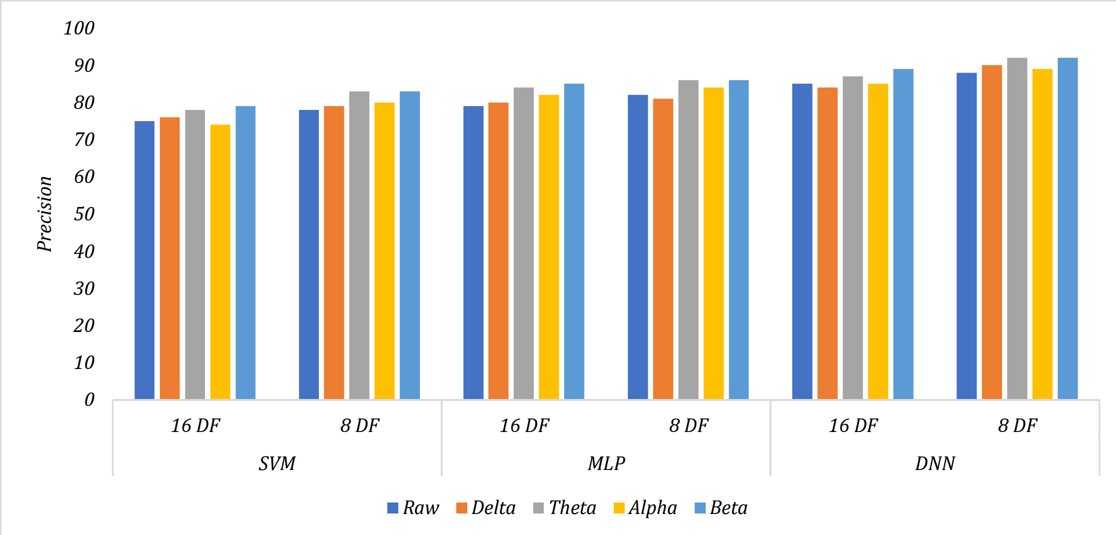

Figure 2: Comparative performance analysis of Precision using SVM, MLP and DNN with 16-dimension and 8-dimension features with signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

Signal	SVM		MLP		DNN	
	16 DF-Dimension Features	8 DF-Dimension Features	16 DF-Dimension Features	8 DF-Dimension Features	16 DF-Dimension Features	8 DF-Dimension Features
Raw	85	88	89	92	95	98
Delta	86	89	90	91	94	96
Theta	88	93	94	96	97	98
Alpha	84	90	92	94	95	97
Beta	89	93	95	96	98	99

Table 3: Comparative analysis of Sensitivity using SVM, MLP and DNN with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

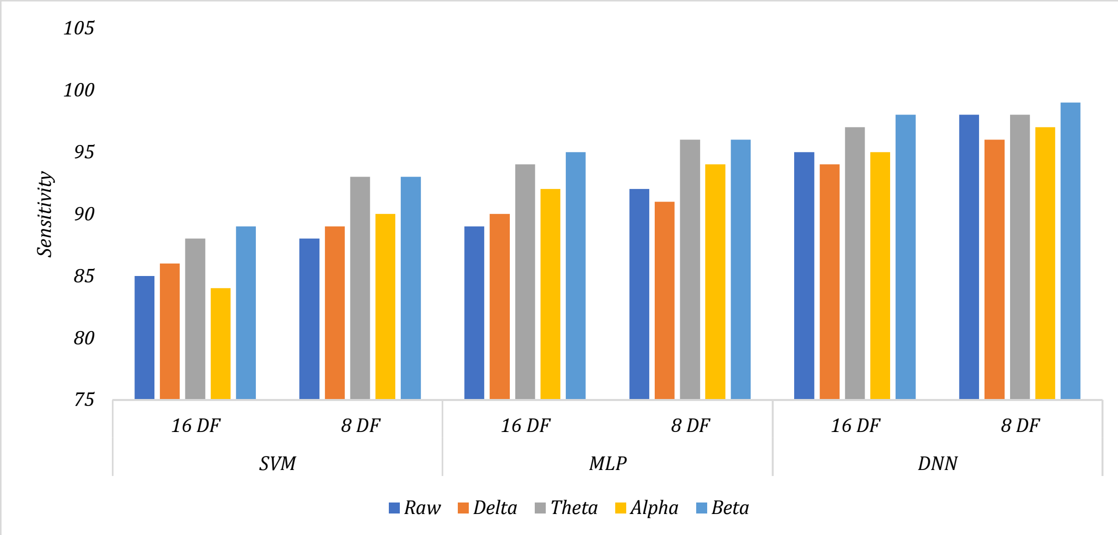

Figure 3: Comparative performance analysis of Sensitivity using SVM, MLP and DNN with 16-dimension and 8-dimension features with signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.

V. CONCLUSIONS & FUTURE SCOPE

The process of motor imagery classification methods faces a problem of detection and recognition ratio of different nervous system diseases. The major issue found in the process of feature extraction and mapping of feature components. For the mapping of feature components applied the methods of swarm intelligence. The swarm intelligence-based algorithm provides the better feature subset for the process of classification. The analysis process suggests MLP based machine learning algorithm is good option for the motor imagery classification.

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