A Review of Motor Imagery EEG Classification Based on Transform

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Abstract

The biomedical play significant role in critical disease detection and prediction. The motor imagery-based EEG classification is the approach to detection some serious disease related to human nervous system. The motor imagery EEG signal data recoded with brain computer interface. The brain computer interface system equipped with electrode and sensors. The recoded signals of nervous system is very complex and high dimension. The complexity of dimension and structure of data face a problem of classification and detection. This paper presents the review of transform based methods of feature extraction of motor imagery classification.

Keywords: EEG Classification, Machine learning, Motor Imagery

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. In the rest part of his paper, section II- literature survey. Section III-discussed the problem domain and finally conclude the conclusions.

II. Literature Survey

Yu Zhang, Guoxu Zhou, Jing Jin, Qibin Zhao, Xingyu Wang and Andrzej Cichocki Et al. [1] Regularization has been one of the most popular approaches to prevent overfitting in electroencephalogram (EEG) classification of brain–computer interfaces (BCIs). The effective-ness of regularization is often highly dependent on the selection of regularization parameters that are typically determined by cross-validation (CV). These limitations substantially deteriorate the system's practicability and may cause a user to be reluctant to use BCIs. In this paper, 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.

Leonard J. Trejo, Karla Kubitz, Roman Rosipal, Rebekah L. Kochavi and Leslie D. Montgomery Et al. [2] Mental fatigue was associated with increased power in frontal theta and parietal alpha EEG rhythms. A statistical classifier can use these effects to model EEG-fatigue relationships accurately. Mean power spectral densities or PSDs and bands rose by 29% and 44%, respectively. A kernel partial least squares classifier trained to classify PSD coefficients (1 - 18 Hz) of single 13-s EEG segments from alert or fatigued task periods was 91% to 100% accurate. For EEG segments from other task periods, the classifier outputs tracked the time course of the development of mental fatigue. By this measure, most subjects became substantially fatigued after 60 min of task performance.

Haider Raza, Hubert Cecotti and Girijesh Prasad Et al. [3] A major problem in a brain-computer interface (BCI) based on electroencephalogram (EEG) recordings is the varying statistical properties of the signals during inter- or intra-session transfers that often lead to deteriorated BCI performances. A filter bank CSP (FBCSP) algorithm typically uses all the features from all the bands to extract and select robust features. In this paper, they 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.

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] Recent studies exploit the neural signal recorded via electroencephalography (EEG) to get a more objective measurement of perceived video quality. Most of these studies capitalize on the event-related potential component P3. They follow an alternative approach to the measurement problem investigating steady state visual evoked potentials (SSVEPs) as EEG correlates of quality changes. Unlike the P3, SSVEPs are directly linked to the sensory processing of the stimuli and do not require long experimental sessions to get a sufficient signal-to-noise ratio.

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). However, EEG is plagued by a variety of interferences and noises, thereby demanding better accuracy and stability for its application in the neuro-prosthetic devices. Here They investigate wavelets and adaptive neuro-fuzzy classification algorithms to enhance the classification accuracy of cognitive tasks. Using a standard cognitive EEG dataset,

James J. S. Norton, Dong Sup Leeb, Jung Woo Leed, Woosik Lee, Ohjin Kwon and Phillip Won Et al. [7] Recent advances in electrodes for noninvasive recording of electroencephalograms expand opportunities collecting such data for diagnosis of neurological disorders and brain computer interfaces. Existing technologies, however, cannot be used effectively in continuous, uninterrupted modes for more than a few days due to irritation and irreversible degradation in the electrical and mechanical properties of the skin interface.

Feifei Qi, Yuanqing Li and Wei Wu Et al. [8] Learning optimal spatio-temporal filters is a key to feature extraction for single-trial electroencephalogram (EEG) classification. The challenges are controlling the complexity of the learning algorithm so as to alleviate the curse of dimensionality and attaining computational efficiency to facilitate online applications, e.g., brain computer interfaces (BCIs). To tackle these barriers, this paper presents 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.

Minho Kim, Byung Hyung Kim and Sungho Jo Et al. [9] This paper describes a low-cost noninvasive brain-computer interface (BCI) hybridized with eye tracking. It also discusses its feasibility through a Fitts' law-based quantitative evaluation method. Noninvasive BCI has recently received a lot of attention. To bring the BCI applications into real life, user-friendly and easily portable devices need to be provided. In this work, as an approach to realize a real-world BCI, electroencephalograph (EEG)-based BCI combined with eye tracking is investigated.

Oana Diana Eva and Anca Mihaela Lazar Et al. [10] Using the EEG Motor Movement/Imagery database there is discussed an off-line analysis for a brain computer interface (BCI) paradigm. 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] Electroencephalogram (EEG) is susceptible to various nonneural physiological artifacts. Automatic artifact removal from EEG data remains a key challenge for extracting relevant information from brain activities. To adapt to variable subjects and EEG acquisition environments, this paper presents an automatic online artifact removal method based on a priori artifact information. The 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.

Younghak Shin, Seungchan Lee, Minkyu Ahn, Hohyun Cho, Sung Chan Jun and Heung-No Lee Et al. [12] In the electroencephalogram (EEG)-based brain-computer interface (BCI) systems, classification is an important signal processing step to control external devices using brain activity. However, scalp-recorded EEG signals have inherent non-stationary characteristics; thus, the classification performance is deteriorated by changing the background activity of the EEG during the BCI experiment. 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. In addition, the SRC has an inherent adaptive classification mechanism that makes it suitable for time-varying EEG signal classification for online BCI systems.

Huijuan Yang, Siavash Sakhavi, 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. Then, they assessed the classification performance of the SRC when the noise power was varied. Using the experimental motor imagery-based EEG and generated noisy test signals, they compared the classification results of the SRC with that of the SVM method, which has been considered as a robust classifier in many BCI studies.

Ye Liu, Qibin Zhao and Liqing Zhang Et al. [14] Motor imagery-based brain computer interfaces (BCIs) training has been proved to be an effective communication system between human brain and external devices. A practical problem in BCI-based systems is how to correctly and efficiently identify and extract subject-specific features from the blurred scalp electroencephalography (EEG) and translate those features into device commands in order to control external devices. In real BCI-based applications, 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.

III. Problem Domain

The extraction of features and band separation from the EEG signals are very difficult. The extraction of features plays important role in detection of some critical diseases related to human brain

1. Loss of features
2. Reduction of Nosie and interference
3. Separation of bands

IV. Conclusion

The motor imagery EEG signal classification is path of complex diseases analysis in medical science. Now a day's various authors and researcher used transform based technique for the categorization of EEG signals. The feature extraction and selection of features in EEG signal play an important role. The extraction of features depends the raw data's behavior. The extraction of features decreases the raw information's size of EEG signal. The wavelet transform based feature extraction methods is better than other feature extraction methods such as CSP and HFE. In future used hybrid feature extraction algorithms for the removal of noise and improve the performance of EEG signal classification.

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