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Literature Survey on Feature Optimization-Based Analysis of Motor Imagery EEG Classification

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***Abstract*— For motor imagery (MI) EEG classification to be more accurate, feature optimization is essential. Through meticulous feature selection and optimization, researchers can improve machine learning algorithms' capacity to differentiate between various motor imagery tasks, such visualizing hand movements. In this paper, different authors work related to feature optimization-based analysis of EEG classification are discussed. This review of the literature will examine the significance of feature optimization in this area, covering a range of feature extraction and selection strategies as well as the effect of feature dimensionality on classification performance.**

Keywords— ***Motor Imagery,Electroencephalography, Brain–Computer Interface, ALS,BCI,MATLAB.***

I. INTRODUCTION

The nervous system is unable to identify every indication of a human body's physical activity. Biomedical engineering is used to track the human body's odd physical behaviour. Visualisation of motors serious brain illnesses like epilepsy and brain stroke can be detected by EEG categorisation. An electropherogram (EEG) is a computer-stored electric recoded signal that is transformed into a digital signal using an A/D converter. Through a brain-computer interface, the entire signal recoding process takes place. Predicting severe disease was a challenge for the intricate structure of the EEG signal. Using the wavelet transform function to extract characteristics from EEG signals is another difficult task. Very-high dimension and noise are the features that were retrieved using transform.

II. LITERATURE SURVEY

In this section work done by different authors in this field are discussed.

Yu Zhang, Guoxu Zhou, Jing Jin, Qibin Zhao, Xingyu Wang and Andrzej Cichocki "Sparse Bayesian Classification of EEG for Brain Computer Interface", IEEE, 2020, Pp 1-13. 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). However, the CV imposes two main limitations on BCIs: a large amount of training data is required from the user and it takes a relatively long time to calibrate the classifier. 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. 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.

This paper introduced a sparse Bayesian method based on a Laplace prior called SBLaplace to classify EEG for BCI applications. The SBLaplace algorithm learns a sparse discriminant vector through hierarchical Bayes modeling of a Laplace prior. The sparsity degree is automatically and quickly estimated from training data under a Bayesian evidence framework. The extensive experimental comparisons were performed between the SBLaplace algorithm and several other competing methods on two EEG data sets. The results demonstrate that the SBLaplace algorithm yields better overall classification performance for ERP-based BCIs, especially for small sample size scenarios. This indicates that the pro-posed method is promising for improving the practicability of BCI systems.

Leonard J. Trejo, Karla Kubitz, Roman Rosipal, Rebekah L. Kochavi and Leslie D. Montgomery "EEG-Based Estimation and Classification of Mental Fatigue", Psychology, 2019, Pp 572-589. 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. Participants (n = 22) solved math problems on a computer until either they felt exhausted or 3 h had elapsed. Pre- and post-task mood scales showed that fatigue increased, and energy decreased. Mean response times rose from 6.7 s to 7.9 s but accuracy did not change significantly. Mean power spectral densities or PSDs and bands rose by 29% and 44%, respectively. The results show that EEG can track the development of mental fatigue over time with accurate updates on a time scale a short as 13 seconds.

Haider Raza, Hubert Cecotti and Girijesh Prasad "Optimising Frequency Band Selection with Forward-Addition and Backward-Elimination Algorithms in EEG-based Brain- Computer Interfaces", IJCNN, 2018, Pp 1-8. Et al. [3] In this paper, forward-addition (FA) and backward-elimination (BE) algorithms are compared in the band selection task of a filter bank CSP approach to BCI design. The FA and BE employ an iterative feature selection approach to select discriminative CSP features from a bank of multiple band-pass filters and spatial filters, and a classification algorithm to classify the selected features. The discussed method addresses the problem of selecting an appropriate subject-specific operational frequency bands for extracting discriminating CSP features. It is shown to be capable of learning subject-specific patterns from the high-dimensional EEG measurements and yields relatively high classification accuracies.

Jeong-Hwan Lim, Jun-Hak Lee, Han-Jeong Hwang, Dong Hwan Kim, Chang-Hwan Im "Development of a hybrid mental spelling system combining SSVEP-based brain computer interface and webcam-based eye tracking" Biomedical Signal Processing and Control, 2020, Pp 99-104. Et al. [4] The goal of this study was to develop a hybrid mental speller that can effectively prevent unexpected typing errors in the steady-state visual evoked potential (SSVEP)-based mental speller by simultaneously using the information of eye-gaze direction detected by a low-cost webcam without calibration. In the implemented hybrid mental speller, a character corresponding to the strongest SSVEP response was typed only when the position of the selected character coincided with the horizontal eye-gaze direction detected by the webcam-based eye tracker.

Laura Acqualagna, Sebastian Bosse, Anne K Porbadnigk, Gabriel Curio, Klaus-Robert Müller, Thomas Wiegand and Benjamin Blankertz "EEG-based classification of video quality perception using steady state visual evoked potentials (SSVEPs)", J. Neural Eng., 2019, Pp 1-17. 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. 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. They tested two different machine learning methods to classify such potentials based on the modulation of the brain rhythm and on time-locked components, respectively.

Dilshad Begum, K. M. Ravikumar, James. Mathew and Sanjeev Kubakaddi "EEG Based Patient Monitoring System for Mental Alertness Using Adaptive Neuro-Fuzzy Approach", Journal of Medical and Bioengineering, 2020, Pp 59-66. Et al. [6] In this paper, wavelet-based feature extraction is incorporated with Adaptive Neuro- Fuzzy Interface System classifier and various clustering and training algorithms got compared. The Neuro-Fuzzy classifier provides the information about the link between input features and the relationship with corresponding classes, adopting data clustering logic to form well-separable groups. The SGM and LM algorithms optimize the network to reduce the

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classification error, and it is seen that the SGM gives better classification results.

James J. S. Norton, Dong Sup Leeb, Jung Woo Leed, Woosik Lee, Ohjin Kwon and Phillip Won "Soft, curved electrode systems capable of integration on the auricle as a persistent brain computer interface", PNAS Early Edition, 2018, Pp 1-6. 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 interfacesHere 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. Experimental and computational studies establish the fundamental aspects of the bending and stretching mechanics that enable this type of intimate integration on the highly irregular and textured surfaces of the auricle.

Feifei Qi, Yuanqing Li and Wei Wu "RSTFC: A Novel Algorithm for Spatio-Temporal Filtering and Classification of Single-Trial EEG", IEEE, 2019, Pp 3070-3082. Et al. [8] 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 "Quantitative Evaluation of a Low-Cost Noninvasive Hybrid Interface Based on EEG and Eye Movement", IEEE, 2020, Pp 159-168. 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 "Comparison of Classifiers and Statistical Analysis for EEG Signals Used in Brain Computer Interface Motor Task Paradigm", International Journal of Advanced Research in Artificial Intelligence, 2018, Pp 8-12. 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 "Automatic Artifact Removal from Electroencephalogram Data Based on A Priori Artifact Information", Hindawi Publishing Corporation, 2019, Pp 1-9. 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. In this study, a priori artifact information acquired online was introduced into WICA to realize automatic artifact removal for variable subjects and EEG acquisition environments. The discussed method was applied to two experiments, namely, motor imagery and emotion recognition. The statistical results showed that their method significantly improved the classification accuracies for motor imagery and emotion recognition. In addition, their method required no reference channels, massive training samples, and visual inspections, so it was entirely automatic. Therefore, the pro-posed method may provide an alternative approach for automatic artifact removal, particularly for novice researchers in other fields.

III. PROBLEM FORMULATION

Band separation and feature extraction from EEG signals are quite challenging. When it comes to identifying certain serious brain disorders, feature extraction is crucial.

- Reduction of Nosie and interference
- Mapping of feature data.
- Loss of features

IV. CONCLUSION

The visualization of motors Classifying EEG signals is a step in the medical science investigation of complex disorders. Many writers and researchers today categorise EEG signals using soft computing techniques. An essential part of the EEG signal is featuring extraction and selection. Features are extracted based on the behavior of the raw data. When features are extracted, the EEG signal's raw information size is reduced. NN, SVM, KNN, and many other algorithms are available under the soft computing umbrella. Optimization methods based on swarm intelligence, including genetic algorithms, PSO, ACO, and many more, are used for feature selection. This paper presents an analysis of categorization algorithms based on comparative analysis. Additionally, the nature of signals is the emphasis of this paper's feature extraction techniques.

REFERENCES

1. Yu Zhang, Guoxu Zhou, Jing Jin, Qibin Zhao, Xingyu Wang and Andrzej Cichocki "Sparse Bayesian Classification of EEG for Brain Computer Interface", IEEE, 2020, Pp 1-13.
2. Leonard J. Trejo, Karla Kubitz, Roman Rosipal, Rebekah L. Kochavi and Leslie D. Montgomery "EEG-Based Estimation and Classification of Mental Fatigue", Psychology, 2019, Pp 572-589.
3. Haider Raza, Hubert Cecotti and Girijesh Prasad "Optimising Frequency Band Selection with Forward-Addition and Backward-Elimination Algorithms in EEG-based Brain- Computer Interfaces", IJCNN, 2020, Pp 1-8.
4. Jeong-Hwan Lim, Jun-Hak Lee, Han-Jeong Hwang, Dong Hwan Kim, Chang-Hwan Im "Development of a hybrid mental spelling system combining SSVEP-based brain computer interface and webcam-based eye tracking" Biomedical Signal Processing and Control, 2020, Pp 99-104.
5. Laura Acqualagna, Sebastian Bosse, Anne K Porbadnigk, Gabriel Curio, Klaus-Robert Müller, Thomas Wiegand and Benjamin Blankertz "EEG-based classification of video quality perception using steady state visual evoked potentials (SSVEPs)", J. Neural Eng., 2019, Pp 1- 17.
6. Dilshad Begum, K. M. Ravikumar, James. Mathew and Sanjeev Kubakaddi "EEG Based Patient Monitoring System for Mental Alertness Using Adaptive Neuro-Fuzzy Approach", Journal of Medical and Bioengineering, 2018, Pp 59-66.
7. James J. S. Norton, Dong Sup Leeb, Jung Woo Leed, Woosik Lee, Ohjin Kwon and Phillip Won "Soft, curved electrode systems capable of integration on the auricle as a persistent brain computer interface", PNAS Early Edition, 2020, Pp 1-6.
8. Feifei Qi, Yuanqing Li and Wei Wu "RSTFC: A Novel Algorithm for Spatio-Temporal Filtering and Classification of Single-Trial EEG", IEEE, 2019, Pp 3070-3082.
9. Minho Kim, Byung Hyung Kim and Sungho Jo "Quantitative Evaluation of a Low-Cost Noninvasive Hybrid Interface Based on EEG and Eye Movement", IEEE, 2019, Pp 159-168.
10. Oana Diana Eva and Anca Mihaela Lazar "Comparison of Classifiers and Statistical Analysis for EEG Signals Used in Brain Computer Interface Motor Task Paradigm", International Journal of Advanced Research in Artificial Intelligence, 2018, Pp 8-12.
11. Chi Zhang, Li Tong, Ying Zeng, Jingfang Jiang, Haibing Bu, Bin Yan and Jianxin Li "Automatic Artifact Removal from Electroencephalogram Data Based on A Priori Artifact Information", Hindawi Publishing Corporation, 2018, Pp 1-9.
12. Younghak Shin, Seungchan Lee, Minkyu Ahn, Hohyun Cho, Sung Chan Jun and Heung- No Lee

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"Noise Robustness Analysis of Sparse Representation based Classification Method for Non-stationary EEG Signal Classification", IEEE, 2018, Pp 1-10.

13. Huijuan Yang, Siavash Sakhavi, Kai Keng Ang and Cuntai Guan "On the Use of Convolutional Neural Networks and Augmented CSP Features for Multi-class Motor Imagery of EEG Signals Classification", IEEE, 2018, Pp 1-4.
14. Ye Liu, Qibin Zhao and Zhang "Uncorrelated Multiway Discriminant Analysis for Motor Imagery EEG Classification", International Journal of Neural Systems, 2019, Pp 1-14.
15. Amirhossein S. Aghaei, Mohammad Shahin Mahanta and Konstantinos N. Plataniotis "Separable Common Spatio-Spectral Patterns for Motor Imagery BCI Systems", IEEE, 2018, Pp 15-29.
16. Luis F. Nicolas-Alonso, Rebeca Corralejo, Javier Gomez-Pilar, Daniel Ãlvarez and Roberto Hornero "Adaptive Stacked Generalization for Multiclass Motor Imagery-based Brain Computer Interfaces", IEEE, 2019, Pp 1-11.