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A proficient and low intricacy EEG motor imagery classification algorithm using boosted decision subspace ensemble learning

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***Abstract*---**Exoskeleton or brain computer interface design is an complicated and challenging effort as it involves many complicated subtasks. Building an synchronized and energy optimized exoskeleton algorithm is the primary objective of this research. In this study the extraction of the frequency band signals from the brain signals are done by the enhanced Morlet Discrete wavelet Algorithm. Further classification of the obtained signals are done through the Boosted Decision Subspace Ensemble Learning (BDSEL) Algorithm. The classified signals are differentiated in to different frequency regions namely alpha, beta, gamma, delta and theta respectively and the accuracy of the acquired signals are checked against the false identification. An enhanced differentiation with high accuracy rate is obtained in this method without trading off with the resolution of the signals. The energy efficiency of the algorithm was proved to be enhanced when compared to the existing Naive Baye's technique. Thus an highly synchronized energy optimized algorithm was designed for a knee exoskeleton system.

***Keywords*---**Exoskeleton, Optimal energy consumption, BDSEL Algorithm, Naive Baye's Algorithm, Discrete Wavelet Transformation, EEG signals.

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Introduction

Brain computer interface (BCI) is an excellent technology in which the where the communication between the neural actions and brain is free from the general muscle neuron information exchange[1-4]. In BCI system the generated patterns or signatures by the brain are extracted through an interfacing machine or robot and processed to produce robot or machine influenced output. In simple words in the people with neuron disease like stroke, has no control over their affected body parts, where the muscle movement should be induced or assisted through an external device. Such assisting or helping robotic device forms exo-skeleton structure. Thus an human and computer interface sets an alternate channel of the communication which is termed as BCI[5-9].

The term soft robot has reached its heights due to the exciting attributes like safe interface with human, adapting to the control signal and enhancing the performance[10].The special soft materials used in the design of the soft robots for human computer interface has hyper elasticity which makes it to perform much better than the traditional rigid robot[11]. Initially the concept of exoskeleton was developed in the US military camps to assist the injured soldiers and to act as an power suit for the soldiers to lift and carry heavy objects[12]. Ralph Moscher designed the first ever exo-skeleton suite which is intended to carry objects weighing more than 250 pounds. That suite was based on the hydraulic and electrical functions. But this suit was found to have some limitation with the speed and its over weighting metal.

In 1965 Mizen developed lighter version of the exo skeleton which has the capability of implementing the human actions with limited degree of freedom. However with the underdeveloped technologies and fewer studies in the field of BCI no successful human robot interface was developed and implemented successfully. After continuous studies and innumerable researches in the year 2012 University of Twente, Netherlands proposed prototype called mindwalker. The ultimate objective of this study was to design an exo skeleton system which could coordinate BCI, virtual reality and control mechanics in a single robotic structure. This prototype had 6 degree of freedoms which was supported by the actuators and springs with hyper elastic property.

In general the design and implementation of BCI for the lower limbs of human body is much rare than that of the upper limb exo skeletons[13]. In these machines the EEG signals are extracted and identified based on the classification algorithms using neural network techniques. Mirroring of the EEG signals are done to classify the right and left side muscle movement during the execution of the machine algorithm in the BCI.

This paper details about the design and development of one such mindwalker exo skeleton which has optimized classification and extraction algorithms.

State of Art

Numerous studies and researches has been carried out in this domain lately. Tingfang et al has done a review study by considering 76 research articles relevant to the control strategies[14]. Among those six control methodologies were considered best performing. But these methods fail to discuss about the BCI techniques and methods. Domen et al made an elaborated study about the sensors used in the extraction of the EEG signals in Exo skeleton robots[15]. Wei et al made a detailed research about the training mode of the asynchronous machine in rehabilitation[16]. However these studies focused only on the exo skeleton used for the rehabilitation purpose and failed to analyze about the other optimizing properties like minimal energy utilization or power consuming operation. Michael et al made an extensive study about the control mechanisms using sensory motors[17]. Although these papers concentrated on the mechanical attributes of the sensory motors and the robotic structure they failed to concentrate on the AI algorithms used for the classification and coordination of the obtained signals. The current article considers the energy optimization algorithms to classify and coordinate the EEG signals in accordance with the muscular movements.

Proposed Methodology

The proposed methodology is a system implementation of the classified brain signals using an ensemble algorithm, Boosted Decision Subspace Ensemble Learning (BDS).

The EEG signals or the brain signals needed for the learning and classification are obtained from the external electrodes placed on the head of the specimen. This method is adopted for the classification of the brain signals as it is simple and cost effective to obtain the signal when compared with the other methods. The temporal resolution of the brain signals are very accurate to the point as the minute variation in the micro electrical activities of the brain are readily captured through the electrodes[18]. The muscular movements and the limb movements of the human body are controlled through motor cortex. This functional region communicates to the corresponding muscles and limbs through alpha motor neurons[19]. This motor activity is responsible to generate the electrical waves to process the thinking of the human brain in the form of brain rhythms. These are classified as the motor imagery signals[20].

The obtained inputs or the EEG signals are pre-processed to remove the irrelevant information to boost up the relevant data. The irrelevant signals or the artifacts have relatively larger amplitude than that of the EEG signals. These artifacts are of two types namely biological and non biological. Biological artifacts are generated from movement of the eyes, movement of cardiac muscle and due to other muscular movements[21].Non biological artifacts are generated due to the spikes in the electrical signals[22]. To filter the required signals Spatio spectro temporal filters are used. These filters are used to improve the signal to noise ratio of the obtained signal.

To extract the relevant information from the processed signals feature extraction is done. For this purpose the signal is classified in to 5 sub bands on different frequency range[23]. The signals are classified as alpha, beta, Gamma, Delta and theta. The specifications of the sub bands are explained as follows.

Delta(δ)

The range of the frequency of the Delta(δ) is from 0.5Hz to 4Hz which is obtained from the Frontal lobe. These signals are generated during the deep sleep and is helpful in measuring the Sleep cycles.

Theta (θ)

Theta frequency plays an important role in the active performance of the brain. These waves are in the band of frequency ranging from 4Hz to 8Hz. This band is specifically found in the brain’s parietal and Temporal lobe region which was found by the researchers Wolter and Dovey in the year 1944. These band of waves are used on the prediction of the corresponding person's action related with the self injuring behaviour.

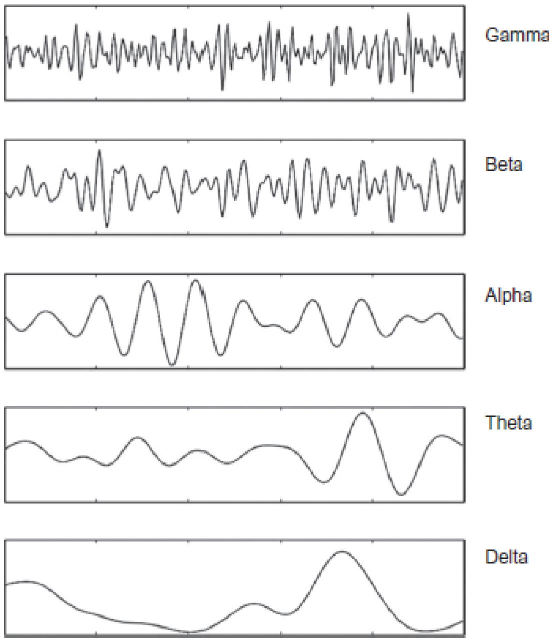

Fig.1. Pictorial illustration of the classified waveforms

Alpha (α)

This band of waves lies in the frequency range of 8Hz to 13Hz. This wave is similar to the first type which can be commonly found in the posterior part of the brain. These waves were discovered by Berger in the year 1929. These waves are classified as upper and lower alpha depending on their frequency bands. These waves are found to be helpful in the analysis of the memory related tasks and attention of the human brain.

Beta (β)

These waveforms are classified in the frequency range of 13Hz - 30Hz which was discovered by Berger in the year 1929. These waves are identified in the frontier and central lobe of the human brain. Usually these waves exhibit amplitude level of 30mV. These waves helps in the investigation of the mental health of the abnormal people. When a brain or region of brain is found to be damaged these waves don't exist.

Gamma (γ)

These waves occur at the frequency range greater than 30Hz and is found by Jasper and Andrews in the year 1938. These waves are very much difficult to record. These waves are used in the investigation of the attention of human brain in terms of cognitive phenomena. When there is some serious disorders like Alzheimer and epilepsy there is irregularity in the occurrence of these waveforms. These waves are usually exhibit minimal amplitude with augmented frequency for the speeding behaviour. Thus cognition is achieved in these waveforms. The pictorial representation of these waveforms are illustrated in the fig.1.

In the proposed methodology the sub-bands are generated using discrete wavelet transformation. The process involved in the sub-bang generation are illustrated in the Fig.2

In this method the obtained waveform is converted in to discrete signals and the corresponding frequency range is obtained by passing them through high pass and low pass filters. Then the required band of frequency is obtained through decomposition of signals using wavelet transform. The resulting output from the high pass filter is called complex coefficient and that from the low pass filter is called approximation coefficients. The operational flow of the extraction of the sub-bands through DWT coefficients are shown in the Fig.2.

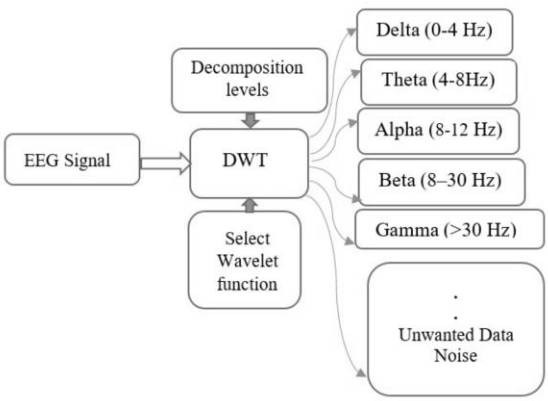

Fig.2. Feature extraction using DWT

Classification

Classification is done to differentiate the brain activities. There are many categorization techniques. The dataset that is used to classify the signals are usually divided as the training set and the test set. Ensemble learning is a machine language algorithm that predicts the datasets by combining the possible predictions. In this proposed model the ensemble algorithm augments the confidence level of the data before prediction. In this model three learners namely ada-boost algorithm, Decision tree and subspace discriminant algorithm are used. The flow chart of the proposed model is shown in the Fig.3.

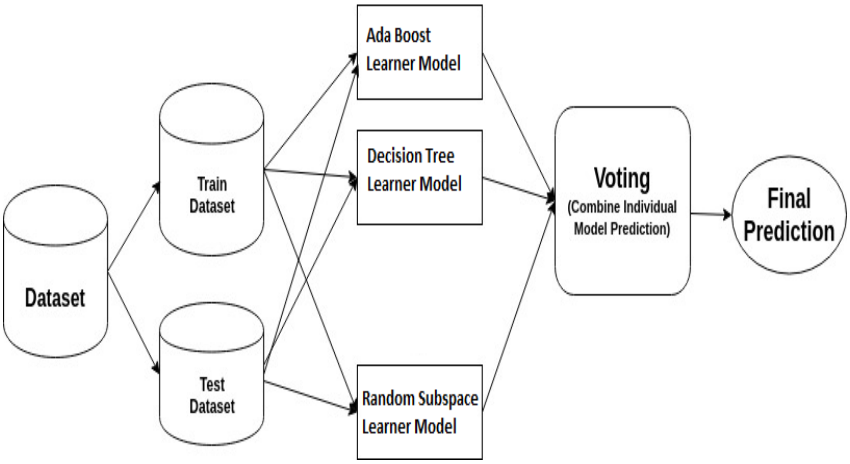

Fig.3. Proposed classification model

The boosting algorithm involves multiple model to complement every other model. Ada boost algorithm is used to weight the instances which is used to estimate the errors. Thus the learning model consistently concentrates on the high weight instances. Initially the algorithm assigns equal weights to all the instances. The learners are forced to classify the instances and the reweighting of the instances are done after classification. Thus the error signals are identified from the new weights.

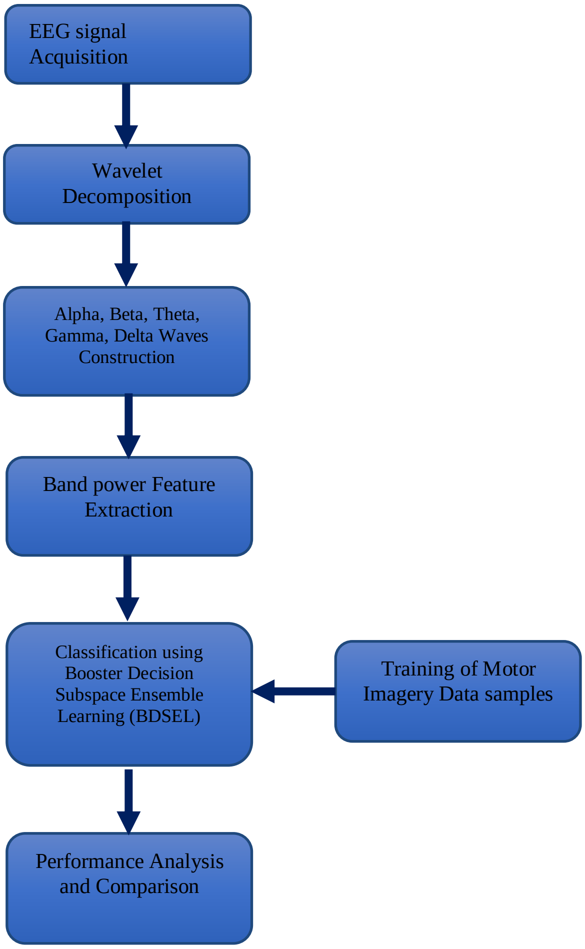

Fig.4. Flowchart of the proposed algorithm

Decision tree algorithm is used to estimate the importance of the extracted features. During node test the value of the feature is compared against a constant. A new sample is classified downwards until it reaches the leaf node. Reduced error pruning (REPTree) algorithm is used to reduce the errors and to improvise the speed optimization of the pruning methods.

Random subspace methodology is used to aggregate the classifiers to produce a better classifier to extract the specific band of signals. Thus the signals are efficiently classified based on the proposed ensemble algorithm. The workflow of the proposed ensemble algorithm is given in the Fig.4.

Results and Discussion

The proposed algorithm is simulated using the MATLAB simulator. The obtained results are compared against the results of the existing technique (Naive Bay's algorithm)

Accuracy

The accuracy is defined as the rate of freedom from defect or false results. This is given as the degree of closeness to the obtained results. From the simulation result the existing technique accuracy is 0.9467 and that of the proposed algorithm is 0.9867. Thus the improved accuracy rate proves the minimal or zero error in the proposed methodology.

Error

The error is obtained by subtracting the accuracy rate from precision 1. The error rate of Naive bays and the proposed method are found to be 0.0533 and 0.0133 respectively. Thus the error in the novel proposed method is approximately zero.

Sensitivity

Sensitivity is the measure of the robustness of the algorithm against the deviating factors. The sensitivity of the existing and the proposed technique is estimated at 0.8933 and 0.9733 respectively. Thus the proposed algorithm is sensitive to the small changes and is capable of recording the false positive outputs effectively.

F1_Score

The F1_score is used to measure the accuracy rate of a algorithm with increased positive predictions. This feature is also inferred as the harmonical mean of the performance metrics like precision and recall. This feature is used to analyse the classification models. Thus the improved f1_score is a measure of the true positive predictions. The F1_score of the existing and the proposed methods are 0.9437 and 0.9865 respectively. This result infers that the prediction of the classification algorithm is higher with augmented performance.

Energy Consumption

The energy consumption of the algorithm is calculated to know the amount of energy required by the algorithm to predict the actions through brainwave signals. The obtained energy consumption of the Naive Baye's algorithms and the proposed BDSEL algorithm is given as 62.6830 and 33.8952 respectively.

Time Complexity

Time complexity is defined as the total time taken by the algorithm to complete the defined task. The time taken by the existing methodology and the proposed methodology is 0.3869 sec and 0.2471 sec respectively. The comparative values of the existing (Naive Baye's) algorithm and the proposed (BDSEL) algorithm is shown illustratively in the Fig.5.

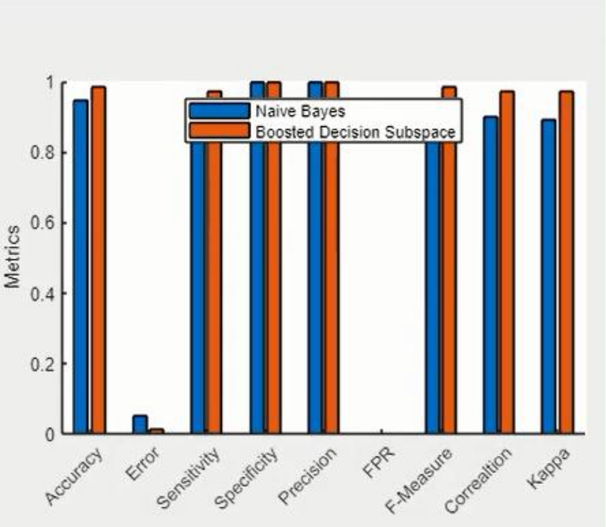

Fig.5. Comparative analysis of the performance parameters

Conclusion

From the obtained results it is evident that the proposed BDSEL algorithm has higher accuracy with minimal false positive rate. This indicates the improved performance efficiency of the proposed algorithm. The energy consumed by the proposed algorithm is very less than the conventional methodology which indicates the optimal energy consumption. The time complexity of the proposed method is very less than that of the Naive Baye's algorithm indicating the reduced time complexity. Thus the proposed methodology is an excellent algorithm that augments the performance efficiency with less energy consumption.

Thus the optimal consumption of the energy gives more residual energy which further increases the lifetime of the battery thereby avoiding the risk of battery outage within few days. This further ensures safety of the user through equipment with long duration batteries. The accuracy of the algorithm with less false negative predictions ensures the errorless performance of the system with more safety of the correct movements.

Reference

[1] Vidal JJ. Toward direct brain-computer communication. Annu Rev Biophys Bioeng. 1973;2:157-180.
[2] Sutter EE. The brain response interface: communication through visuallyinduced electrical brain responses. J Microcomput Appl. 1992;15:31-45.
[3] Wolpaw JR, McFarland DJ, Vaughan TM. Brain-computer interface research at the Wadsworth Center. IEEE Trans Rehabil Eng. 2000; 8(2):222-226.
[4] Felzer T. On the Possibility of Developing a Brain-Computer Interface (BCI). Darmstadt, Germany: Department of Computer Science, Technical University of Darmstadt; 2001.

[5] Donoghue JP. Connecting cortex to machines: recent advances in brain interfaces. Nat Neurosci. 2002;5(suppl):1085-1088.

[6] Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clinic Neurophysiol. 2002;113(6):767-791.

[7] Mason SG, Birch GE. A brain-controlled switch for asynchronous control applications. IEEE Trans Biomed Eng. 2000;47(10):1297-1307.

[8] Vaughan TM, Heetderks WJ, Trejo LJ. Guest editorial braincomputer interface technology: a review of the second international meeting. IEEE Trans Neural Syst Rehabil Eng. 2003;11(2):94-109.

[9] Dornhege G. Toward Brain-Computer Interfacing. Cambridge, MA:MIT Press; 2007

[10] Rus, D.; Tolley, M.T. Design, fabrication and control of soft robots. Nature 2015, 521, 467–475

[11] Mori, Y.; Wakayama, T.; Wada, A.; Kawamura, S. A Fully Multi-Material Three-Dimensional Printed Soft Gripper with Variable Stiffness for Robust Grasping. Soft Robot. 2019, 6, 507–519

[12] Kazerooni, H. (2006). Steger, R., & Huang, L. The International Journal of Robotics Research, 25(5-6), 561–573. doi:10.1177/0278364906065505

[13] W. Michael, G. Martin, C. Oliver, R. Stephan, and B. Philipp, Active lower limb prosthetics: a systematic review of design issues and solutions, Biomedical Engineering Online, 15(3), 2016, 140.

[14] Y. Tingfang, C. Marco, O.C. Maria, and V. Nicola, Review of assistive strategies in powered lower-limb orthoses and exoskeletons, Robotics and Autonomous Systems, 64,2015, 120–136.

[15] N. Domen and R. Robert, A survey of sensor fusion methods in wearable robotics, Robotics and Autonomous Systems, 73, 2015, 155–170.

[16] M.Wei, L. Quan, Z. Zude, A. Qingsong, S. Bo, and X.S. Shane, Recent development of mechanisms and control strategies for robot-assisted lower limb rehabilitation, Mechatronics, 31,2015, 132–145

[17] M.R. Tucker, O. Jeremy, P. Anna, B. Hannes, B. Mohamed, L. Olivier, D.R.M. Jos´e, R. Robert, V. Heike, and G. Roger, Control strategies for active lower extremity prosthetics and orthotics: a review, Journal of Neuroengineering and Rehabilitation, 12(1), 2015, 1.

[18] R.P.N. Rao, Brain-Computer Interfacing: An Introduction, Cambridge University Press, Cambridge, 2013.

[19] Gogeascoechea, Antonio and Kuck, Alexander and van Asseldonk, Edwin and Negro, Francesco and Buitenweg, Jan R. and Yavuz, Utku S. and Sartori, Massimo "Interfacing With Alpha Motor Neurons in Spinal Cord Injury Patients Receiving Trans-spinal Electrical Stimulation", Int. journals of Frontiers in Neurology, Vol 11, 2020. Issn-1664-2295.

[20] G. Pfurtscheller, C. Neuper, Motor imagery and direct brain-computer communication, Proc. IEEE 89 (7) (2001) 1123–1134.

[21] C.L. Phillips, J.M. Parr, E.A. Riskin, Signals, Systems, and Transforms, Prentice Hall, Upper Saddle River, NJ,2013.

[22] R. Chatterjee, T. Bandyopadhyay, D.K. Sanyal, D. Guha, Comparative analysis of feature extraction techniques in motor imagery EEG signal classification, in: Proceedings of First International Conference on Smart System, Innovations and Computing, Springer, New York, NY, 2018, pp. 73–83.

[23] Christoph S Herrmann, Maren Grigutsch, and Niko A Busch. 11 eeg oscillations and wavelet analysis. Event-related potentials: A methods handbook, page 229, 2005.

[24] Abdulhamit Subasi. Eeg signal classification using wavelet feature extraction and a mixture of expert model. Expert Systems with Applications, 32(4):1084–1093, 2007.

[25] Lina Wang, WeiningXue, Yang Li, MeilinLuo, Jie Huang, Weigang Cui, and Chao Huang. Automatic epileptic seizure detection in eeg signals using multi-domain feature extraction and nonlinear analysis. Entropy, 19(6):222, 2019

[26] N. Brodu, F. Lotte, A. L_ecuyer, Comparative study of band-power extraction techniques for motor imagery classification, in: 2021 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB), IEEE, 2021, pp. 1–6.