

A REVIEW ON BRAIN COMPUTER INTERFACE OF MUSCLE MOVEMENT CLASSIFICATION FOR THE UPPER LIMBS

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Abstract: Brain Computer Interface (BCI) encompasses an amalgamation of the brain and computer for sharing an interface which could be used as a communication channel between them. Bio-signals are extracted with the help of electrodes by EMG from muscle, EEG from brain, EOG from eyes etc. but these signal are not much useful as they are very small in magnitude and contain noises. For getting meaning information from the noisy and highly non-linear signals classification of the data has to be done. This paper studies the different artificial intelligent methods of BCI for the classification of signals for the upper limb. The methods included in this study are SVM, Random Tree, Neural Network, Time Domain Power- Spectral Analysis, Ultra Sound Images, Icasso clustering and some hybrid classifiers.

Keywords: BCI, ANN, SVM, EMG, sEMG

I. INTRODUCTION

The human brain has unmeasurable amount of neurons with innumerable connections between them for the transmission of bio-signals. An electrode chip called electrode can be superficially placed or injected for the acquisition of these signals. These signal acquired is a small magnitude electrical signal with noises and non-linearity. These signals are filtered and useful information is extracted with the help of Artificial Intelligent Methods. Brain Computer Interface is a direct interface of communication between the complex computer and a more complex brain. Bio-signals like EEG, EMG, EOG etc. is utilized for BCI[1].

Tiny variations between neurons are voltages measured and signals are augmented for proper representation through graphs. With Invasive BCIs' main focus on straight application into the cerebrum or the grey matter of the brain so that a better quality signal can be generated for neurosurgery, Non Invasive BCIs uses techniques like Electroencephalography (EEG), Magneto Encephalography (MEG)[2][3] and function Magnetic Resonance Imaging (fMRI)[4], [5]. BCI has played a pivotal role in emerging intelligent relaxation devices, enhanced devices for controlling of wheelchairs, exoskeletons and vehicles an extraordinary example of BCI is the Bionic eyes which can be used to restore eyesight for people suffering vision loss[6][7][8].

A basic flowchart of BCI is shown in fig 1. Signal is acquired by various means and then filtered and noise is removed from it. Information is extracted with the help of feature extraction and classification. Classification plays a very important role in extracting the information or machine learning as conclusions are drawn based on the classification of the data it already has and then use these conclusions for the categorization of the new data it receives [3][9]. It helps in determination of the category of the new data point effectively and efficiently. A classification model is developed based in the training dataset and label corresponding it.

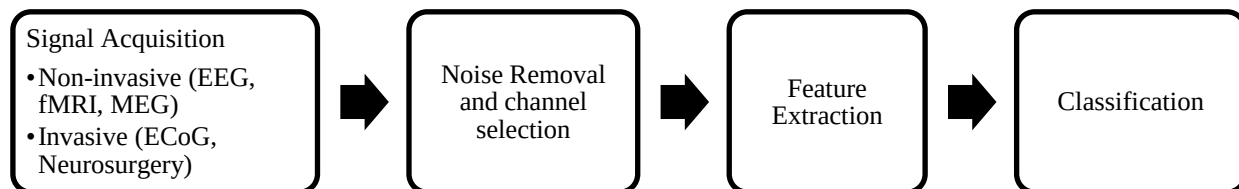


Fig.1. Flowchart of Brain Computer Interface

This paper discuss the various artificial intelligent methods for the classification of bio-signals like SVM, Random Tree, Neural Network, Time Domain Power- Spectral Analysis, Ultra Sound Images, Icasso clustering and some hybrid classifiers. Various inferences are drawn from and each method is examined for its fastness and classification accuracy.

II. Various Artificial Intelligent methods for classification of Bio-signals

With the advent of Artificial Intelligence, the problems faced while working with bio-signals are solved. The artificial intelligent classifiers give better results and thus are effectively used in bio-signals. Some artificial intelligent classifiers which are used for the classification of signals of upper-limb are discussed below:

1. Linear Discriminant Analysis (LDA)

Rescio et al., in [7] illustrated the classification phase that has been obtained by Linear Discriminant Analysis which have a low cost of computation and a high accurate classification. The system established has a high performance for specificity and sensitivity (about 90%) in controlled circumstances. Thus, the possibility for a fast and wearable sEMG unbalance discovery system, by means of Machine Learning is confirmed. Fall of the initial phase can be easily recognized which increases the decision making time and thus it also minimize the inappropriate and unsuitable activations of the protection system, in actual life situation.

Baker, et al., in [10] proposed parallel LDA based algorithm which can work offline for decoding finger activity on the basis of features extracted from recorded EMG with frames continuously presented. This offline parallel LDA is made to run for intra-day sessions and for sessions for which training of algorithm is done for a day and testing is done for the succeeding days. The evaluation of the algorithm's performance is done continuously by matching the classification yield of algorithm with the existing state of the finger switches.

2. Support Vector Machine (SVM)

Wahid, et al., in [11] used upper limbs EMG for recognizing the hand gestures in which the measurement of the skeletal muscle's electrical activity is measured. Generalization of the muscle activity for different subjects using EMG signals for a certain hand gesture is always puzzling. Mean absolute value, slope sign change, zero crossing, and waveform length are the four basic time domain features extracted from the active EMG signals of each channel. Five machine-learning algorithms, namely, Naïve Bayes (NB), Discriminant Analysis (DA), Random Forest (RF), *k*-Nearest Neighbor (*k*NN) and Support Vector Machine (SVM) were used for the classification of different hand gestures.

Levitt, et al., in [12] proposed an automated quantitative SVM-based algorithm for accurate classification artifact EEG epochs in three classes of subject i.e. awake humans, canine and rodent subjects. This technique also aided in the determination of the state of eyes whether closed or open. The SVM accurateness for classification in humans, beagle dogs and Sprague Dawley rats were 94.17%, 85.37%, and 83.68%, respectively. For 'eyes closed or open' states in humans its correctness was 88.60%.

Bochniewicz, et al., in [13] described a novel method which shows assurance for low-cost and impartial assessment of the use of functional Upper Extremity in hemiparesis, and evaluation of its influence of Upper Extremity treatments. A raw sensor data is used for the training of a classifier, and assess whether the patients functionally use their Upper Extremity or not can be done distantly. For the rehabilitative treatment trial setting, an intra-subject test/train tactic would be particularly correct.

Timemy, et al., in [14] suggested the utilization of multichannel sEMG for the classification of individual as well as collective finger movements for handy prosthetic control. The sEMG signals were recorded for six below-elbow amputee and ten intact-limbed persons. Offline processing was used for the evaluation of the classification performance.

Mesa, et al., in [15] were interested in selection of a condensed group of sEMG channels and the features of the signal that will be capable of providing a more accurate classification rate for any user in a myoelectric control system. As a conclusion, the position of 32 sEMG electrodes that can be placed around-along the forearm and 86 signal-features are assessed concurrently for a task of classification of static-hand gesture (14 different gestures).

Chen, et al., in [16] concentrated on acknowledgment of movement of upper arm and gross hand and some effort on the classification of distinct finger movements such as finger typing tasks. This paper focuses on the acknowledgment of numerous gestures based on a 4-channel wireless sEMG system.

Zhao, et al., in [17] proposed a sEMG based quantitative analysis method to estimate movement of human joints, which was useful for the control of rehabilitation process for the upper limb this robotic system uses participants own arm. SVM is used for the establishment of quantitative model.

Figueredo et al [18] combined dimensional data reduction, normalization technique and cross validation with SVM for automatic recognition of subject's clinical status. It offers an objective and rapid tool for that and its future direction consists of its real time application for driving power assistive devices.

3. Random TREE

Raj et al [19] proposed a new classifier and named it Apriori best probability tree classifier which can predict the movement of human in the indoor environment. This apt classifier is amalgamated with bagged 348 machine learning algorithm that has resulted into an ensemble method which can predict future human movement. Pattern mining is done on the basis of spatial, temporal and social data for adding more accuracy. Thus, this model can also detect any abnormal pattern based on its clustering mechanism.

4. Artificial Neural Network

Tsemov et al [20] have used neural network for the identification of the forearm activity based on EMG pattern and comparison is done with different intelligent computational method of identification.

Naik et al [21] exploited the sparse and additive nature of signals by extracting the reliable and accurate measurement of sEMG feature using minimum number of sensors. ANN classification scheme is used for the classification of signals through simple and complex finger flexion. On comparing the simulation and experimental studies it was found dirty classification of 10 finger flexion can be done with 92% accuracy when recorded with two sEMG channels.

5. Time Domain Power- Spectral Analysis

Timemy in [22] used Time Domain Power Spectral Descriptors (TD-PSD) for the classification of 8 hand and finger movements and finding the best feature among them.

Khusaba, et al., in [23] proposed a new framework for feature extraction which aims to provide a better representation of muscular activities by increasing the amount of information extracted from the combined and individual EMG channels. They proposed the use of Time Domain Descriptors (TDD) for the estimation of power spectrum characteristics of the EMG signals so that the need of computational power for the construction of spectral features can be reduced.

Reaz, et al, in [24] used various algorithms and methodologies for the analysis of EMG signal so that an efficient and effective way for exploring the signal and its nature can be achieved. Hardware implementation for gress recognition, prosthetic hand control and human computer interaction is pointed out.

6. Ultra Sound Images

Sikdar, et al., in [25] proposed a control strategy based on Ultrasound imaging for the controlling of upper arm prosthetics which can overcome many limitations of myoelectric controller the prosthetics. A wearable mechanically scanned single element ultrasound system is used for obtaining the real time ultrasound images of the forearm muscle and they are used to create the maps for the muscular activity based on the change in Echo of the ultrasound during the contraction of the muscle.

7. Hybrid Classifier

Peleg, et al., in [26] proposed a genetic algorithm optimized SVM as a simple classifier for the classification of the EMG signals recorded from the two pairs of electrode placed on the arm for operating the prosthetics. Multiple features are extracted from the signals and the most relevant feature is obtained by using GA.

Lajnef, et al., in [27] proposed hybrid multiclass SVM with decision tree approach for a sleep Staging framework. Electroencephalogram, electrooculogram and electromyogram recordings are done for 15 patients and frequency domain feature extraction is done. Classification of the signal features is done with the help of K fold cross validation.

Gravitational search algorithm is used for the optimization of SVM so that a better fitting accuracy and generalization ability can be achieved by SVM. From the simulation of experiments, it can be deduced that the proposed GSA- SVM has better results. With initial online experiment the proposed method turned out to be more feasible.

8. Comparative Analysis studies

Wang, et al., in [28] propose the prosthetic hand which can be controlled by sEMG signals from two electrodes only. It has a very compact structure with 4 degrees of freedom and five fingers controlled by four independent actuators. Employment of pattern recognition is done where sample entropy, fourth order autoregressive Coefficient, variance (VAR), Mean Absolute value (MAV) are used for optimal feature set LDA is used for reducing the dimensions.

Geethanjali, et al., in [29] propose an indigenous system by using sEMG signals in the laboratory. A signal conditioning device is developed and a digital signal controller is used for the pattern recognition and the generation of control signal for the actuation of hand. The EMG signals are acquired for ten healthy subjects and six amputees for six hand movements. Different classifiers like simple Logistic regression (SLR), decision tree, neural network, linear discriminant analysis and Logistic model trees are also studied for the performance.

Karthick, et al., in [30] has done the analysis to differentiate between the fatigue and non-fatigue conditions of the dynamic muscle. 12 features are extracted and the most prominent feature is optimised using GA and binary PSO. The classification accuracy of 5 machine learning algorithms namely support vector machine of polynomial and radial basis kernel, naïve Bayes, rotation forest and random forest is done.

Anam, et al., in [31] compared ELMs (Extreme Learning Method) with other classifiers such as k nearest neighbour (kNN), Linear Discriminant Analysis, Least Square-SVM and SVM. RBF-ELM is as accurate as LSSVM and SVM but faster. It also gives the accuracy of 98.55 on amputees and 99.5 on non-amputees when six channel EMG is used.

III. Conclusion

A number of Artificial Intelligent methods are present for the classification of the bio-signals. For Linear Discriminant Analysis, classification phase is attained through a little computational cost but with a high classification accuracy level. RBF-ELM is as accurate as SVM and LS-SVM but faster than the SVM family; it is superior to LDA and kNN. Normalization of the raw data and its usage for the training of the classifier gives more accurate results. Amalgamated machine learning methods or ensemble methods can be used for the future movement prediction and its assessment.

Multichannel sEMG can be used for the classification of combined and individual finger movements which can be used for intelligent prosthetics. But with the decreases in the channels for the recording of physical sEMG channels, the recording device of sEMG become simpler, cheaper and thus reduces the dimensions of the vectors of variables presented for classification. It therefore, reduces the training examples and, additionally, the classifier needs less memory and computational power. Hybrid SVM like GA-SVM, GSA-SVM etc. has given better classification results and thus can be used for better classification accuracy

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