International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Transcutaneous Electrical Nerve Stimulation for Musculoskeletal Disorder Using EEG

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ABSTRACT ---

Brain Computer Interfaces (BCI's) give their users communication and control channels that do not depend on the brain's normal output channels of peripheral nerves and muscles. Current interest in BCI development comes mainly from the hope that this technology could be a valuable new augmentative communication option for those with severe motor disabilities—disabilities that prevent them from using conventional augmentative technologies, all of which require some voluntary muscle control. The BCI research groups are focusing on brain electrical activity, recorded from the scalpas Electro Encephalo Graphic activity (EEG) or from within the brain as single-unit activity, as the basis for this new communication and control technology.The EEG signals are the recording of electrical signal emanating from the brain that are utilised for the diagnosis of brain disorders and the development of prosthetic devices for movement restricted people, which is broadly classified as Brain machine interface (BMI) or Brain computer interface (BCI). BCI employs the EEG signal analysis for developing a direct communication link between the human brain and the computer. BCI systems enable individuals with severe motor disabilities to independently use computers, speech synthesisers, assistive appliances, and neural prostheses. Even though EEG signals provide an effectual analysis of brain functionality for BCI, it shows dissimilarity between individuals. The dissimilarity among individuals arises on account of physiological differences. The presence of artifacts in EEG signals further makes the EEG signal analysis a difficult task. EEG signals are processed in BCI applications to extract the frequency components and monitor their variations and classify the different Motor Imaginary (MI) activities explores signals decomposition methods for identifying the power variations in EEG signals for classifying the MI activity. The main challenges addressed include evolving with a feature extraction method for perceiving the ERD/ERS in EEG signals, a classifier that could be applied irrespective of EEG signal variability among subjects. Four methods for MI classification are proposed for feature extraction based on the four modal decomposition methods Dynamical Mode Decomposition (DMD), Variational mode decomposition (VMD), red Empirical wavelet transform (EWT), and tensor decomposition. The features in the form of EEG spectrum image generated from VMD and STFT provides a novel method for analyzing the power variations in EEG for MI applications. From the study conducted, VMD outstands in terms of better accuracy among the four modal decomposition methods when classified after feature extraction from EEG signals. An average accuracy of 91.37% 94.41% , 85.66% and 90.20% across subjects is obtained for the four datasets used in the work.

Keywords- EEG, BMI, BCI, EWT

I. INTRODUCTION

Brain Computer Interface (BCI) is a communication system, which enables the user to control special computer applications using thoughts. The general purpose BCI system takes neural signals as its inputs, which is the fundamental element of any BCI system and then to process this signal, extracting features from it, then classifying them and consequently converting these recognized signals into device control commands and invocation of the desired actions.

The acquired EEG signals are preprocessed by filtering. Pre-processing involves the removal of muscle and eye artifacts from the signal. In the case of Motor Imaginary (MI) classification, the EEG signals acquisition involves during imagination of movements by a subject wherein the subject is in a relaxed state. Hence the muscle artifacts are negligible in this context. In addition to this, the dataset used in this work is prepared after the visual removal of artifacts. The next step involves feature extraction for which numerous time, frequency, or time frequency methods are adopted. After feature extraction, the classification is performed to identify the activity. A block diagram illustrating the methods involved in developing a BCI system from EEG signals is provided in Figure 1.1 MI is a class of signals studies in which EEG signals recorded during imagination of a particular task is analysed for recognising or predicting the intention. Identification of which body part is imagined to move from the EEG signals acquired during the imaginary movements has attracted researchers for the last two decades (Alamdari et al. (2016)).

This motor imaginary based BCI systems make use of ERD or power decrease and ERS or power increase in the sensori cortex area of the brain. The ERD is evident in the contralateral region prior to the voluntary movement or imagination of movement and extends out bilaterally before execution of movement and follows ERS activity after the movement. The amplitude of oscillations decreases as the frequency increase because the frequency of oscillations is negatively correlated with their amplitude (McFarland et al. (2000); Pfurtscheller et al. (2000)) and the BCI systems based on these variations are classified as Sensorimotor rhythm based BCI. The ERD and ERS activities extracted from the EEG signals are highly frequency specific and are observed in the Mu (9 − 13Hz) and Beta (14 − 30Hz) rhythms. The rhythmic activity seen in the brain is detectable

in healthy individuals as well as in individuals with injuries or even in individuals with movement restrictions (Vallabhaneni et al. (2005); Yuan and He (2014)). voluntary movement or imagination of movement and extends out bilaterally before execution of movement and follows ERS activity after the movement. The amplitude of oscillations decreases as the frequency increase because the frequency of oscillations is negatively correlated with their amplitude (McFarland et al. (2000); Pfurtscheller et al. (2000)) and the BCI systems based on these variations are classified as Sensorimotor rhythm based BCI. The ERD and ERS activities extracted from the EEG signals are highly frequency specific and are observed in the Mu (9 − 13Hz) and Beta (14 − 30Hz) rhythms.

These patterns could be created by one of the two BCI approaches. One approach requires the BCI user to concentrate on a mental task to produce a brain pattern that identifies with the required control i.e., imagining hand movement. Performance of different mental tasks result in various EEG responses which can be translated into a control code book for the user, if one can ensure, the BCI system will decipher EEG activity. The next approach requires users to undergo 2 extensive training so that an EEG related self-regulatory ability is developed i.e., the mu rhythm. When a user generates 'distinguishable' brain activity in tandem with different control commands, the next aim of the BCI system is to recognize this EEG activity and extract features or signal characteristics which tally with specific control differentiating it from control command related activity. The fundamental requirement of BCI [1] is to identify control/communication attempts from EEG signals by attributing values associated to characteristic activity. Successful BCI operations require the user to control activity that generates these signal features so that BCI correctly understands the user's intentions.

II. RELATED WORK

2.1. LITERATURE SURVEY

The first step towards a system for thought process recognition is motor imaginary identification, where the subject's imagination of moving a body part is identified based on the features extracted from EEG signals. For discriminating the activity imagined by a subject, EEG signals are analysed in time, frequency or in time-frequency domains. The information extracted are either spontaneous signal or evoked potential which appear in EEG (Padfield et al. (2019)). In the category of spontaneous signals, ERD activity observed in the Sensorimotor cortex region of the brain represents suppression of the mu band of EEG signals during the imagination of an activity in response to stimuli. The suppression is possible due to imaginary movement, actual movement or due to some memory tasks. In the case of imaginary movement, after suppression of mu-beta band, a synchronisation activity ERS appears which results in power increase in mu beta-rhythm (Pfurtscheller and Da Silva (1999)). The ERD and ERS activities appear in the contralateral side of the brain, which then spread to the ipsilateral side. This can be harnessed for controlling devices (Wolpaw and McFarland (1994)).The effectiveness of EEG for decoding the intended activity of a person is analysed based on the time frequency information (Sleight et al.

(2009); Wang and James (2007); Yong et al. (2005)), The rhythmic activity seen in the brain detectable healthy individuals as well as in individual with injuries or even in individuals with movement restrictions (Vallabhaneni et al. (2005); Yuan and He (2014)). Essentially, BCI monitors brain activity (via brain imaging technology) and detects characteristic brain pattern alterations which the user controls to correspond (through digital signal processing algorithms) to the world. In BCI, messages and commands are expressed through electro-physiological signals generated in the brain and not through muscle contractions as in conventional communication methods. Such communication naturally needs brain activity patterns that can be consciously generated/controlled by a subject and ultimately which a computer system can distinguish. Electroencephalography (EEG) based BCI systems decode patterns of electrical signals from the human scalp. frequency domain information (Navarro et al. (2005)) and the power spectrum analysis of EEG signals (Caracillo and Castro (2013); Lal et al. (2005); Saa and Gutierrez (2010)),(Bashashati et al. (2007)). The power spectrum analysis remained as one of the foremost method for feature.

The signal decomposition methods create sub signals of the multimodal signals. A comparison of three signal decomposition methods, EMD, WPD and Wavelet transform were used to find the subsignals from EEG for MI classification. The features extracted from the subsignals are the 6 statistical features (Kevric and Subasi (2017)). The classification with k-NN results suggests wavelet transform outperformed other methods with highest accuracy of 92.8%. IMF from EMD could be alternative for studying ERD and ERS was demonstrated in (Ortiz et al. (2020)). In this study two analysis were carried out on IMF. First analysis involves calculating power variations in IMF's consider previous rest state as reference. While the second analysis involves calculating the rhythms from instantaneous variation in time. The conditional EMD (Tang et al. (2020)) is applied on EEG signals and the relevant IMF are chosen using correlation coefficient between EEG signal as well as between IMF. The classification using the one-dimensional multi-scale CNN provides improvement in accuracy compared with the state of art methods.

2.2 GENERAL TRENDS IN BCI

BCI provides a communication path between human brain and the computer system. With the advancement in the areas of information technology and neurosciences, there has been a surge of interest in turning fiction into reality. The major goal of BCI research is to develop a system that allows disabled people to communicate with other persons and helps to interact with the external environments. This area includes components like, comparison of invasive and non-invasive technologies to measure brain activity, evaluation of control signals (i.e. patterns of brain activity that can be used for communication), development of algorithms for translation of brain signals into computer commands and the development of new BCI applications. Hs, A., et al., [22] provided an insight into the aspects of BCI, its applications, recent developments and open problems in this area of research

BCI systems require correct classification of signals interpreted from the brain for useful operation. To this end

Daly, I. et al., [23] investigated a method proposed to correctly classify a series of images presented to a group of subjects. It showed that is possible to use the proposed methods to correctly recognize the original stimuli presented to a subject from analysis of their EEG. Additionally, used a verification set to show that the trained classification method can be applied to a different set of data. Then went on to investigate the issue of invariance in EEG signals. That is, the brain representation of similar stimuli is recognizable across different subjects. Finally, it is considered that the usefulness of the methods investigated towards an improved BCI system and discussed how it could potentially lead to great improvements in the ease of use for the end user by offering an alternative, more intuitive control based mode of operation.

The problems that impede transferring the successful

BCI research results to the outside world are highlighted by Alwasiti, H. H., et al., [24]. The main problems can be classified into two distinct parts, first, the sensory interfacing problems and second, the reliability of the different classification algorithms for the EEG patterns.

Potential future applications for this technology have been addressed. Amiri, S., et al., [26] introduced several types of BCIs and their combinations, then reviewed and discussed hybrid BCIs, different possibilities to combine them and their advantages and disadvantages. Conventional BCIs have not become totally applicable, due to the lack of high accuracy, reliability, low information transfer rate and user acceptability. A new approach to create a more reliable BCI that takes advantage of each system is to combine two or more BCI systems with different brain activity patterns or different input signal sources. This type of BCI, called hybrid BCI, may reduce disadvantages of each conventional BCI system. In addition, hybrid BCIs may create more applications and possibly increase the accuracy and the information transfer rate. However, the type of BCIs and their combinations should be considered carefully.

Fourier Transform (FFT). Dynamic mode decomposition (DMD) is a new matrix decomposition which takes in a time series data and computes a set of dynamic modes thus the algorithm can be seen as a data-decomposition technique that allows the extraction of dynamically relevant features from numerical data. The method was first applied in fluid mechanics where DMD modes was found to predict the fluid flow and thus model the flow. Earlier the snap shot based flow of fluids were studied based on POD (Kutz (2013)). The method was popular since it provided mutually orthogonal spatial structures and it was very popular as it worked on experimental and numerical data.The disadvantage of the method being the inability to extract the temporal dynamics. This POD structures are widely used in model reduction and have shown significant success in feedback control applications (Tu et al. (2013)). In addition to application to fluid flow, DMD was used for fore ground back ground separation of video from high-speed cameras (Grosek and Kutz (2014)). DMD decomposes nonlinear data into modes and these modes provide a combined spatialtemporal description of the signal. DMD was first applied in studies of the nonlinear modeling (Schmid et al. (2011)). EEG is a nonlinear signal with underlying nonlinear dynamics (Lainscsek et al. (2013)).

Each of the modes are associated with a complex eigenvalue.

The spatial-temporal modes of DMD can be derived using Eigen decomposition method Kutz (2013). This enables the use of DMD in wide variety of applications (Schmid et al. (2011)). The potentiality of DMD is found in exploiting the intrinsic low-dimensionality of a complicated system (Tu et al. (2013)). This helps to model the system in a more computationally and theoretically tractable form. DMD power obtained from the modes matches to Fourier power of the signal (Brunton et al. (2016)). Many BCI systems based on EEG provide training for subject so as to have better brain rhythmic activity. Training session involves long hours which make the subjects tired (Yuan and He (2014)). It has always been a challenge to have more appropriate analysis so as to obtain a more appreciable feature for classification of brain signals.

Time-frequency techniques remain as one of the recognised methods for analysing the non-stationary, nonlinear physiological signals like EEG, the benefits being able to study the instantaneous frequency variations of the signal. Feature extraction for MI identification using Multivariant Empirical Mode Decomposition (MEMD) and STFT has shown better performance compared to Discriminative Frequency Band Common Spatial Pattern (DFBCSP) (Bhattacharyya and Mukul (2018b); Kevric and Subasi (2017); Park et al. (2013a)). Two extensional versions of EMD viz VMD and EWT have been recently proposed (Dragomiretskiy and Zosso (2014); Gilles et al. (2013)). These methods address the shortcomings in EMD like sensitivity to noise and mode mixing by having strong mathematical theory (Dragomiretskiy and Zosso (2014); Gilles et al. (2013)) and finds applications in diverse fields like speech enhancement (Gowri et al. (2016), hyperspectral images Mol et al. (2015)), digital forensic (Premjith et al. (2015)) and in frequency estimation (Prakash et al. (2016)). VMD decomposes the real valued multicomponent signal into subsignals adaptively using the calculus of variation.

This iterative process of decomposition provides number of bandlimited modes of the input signals along with strong frequency supported center frequencies for each mode. The advantage of VMD over EMD for denoising physiological signals like EEG from rats (Lahmiri and Boukadoum (2015)) and ECG from human have been studied (Prabhakararao and Manikandan (2016)). Estimation of the glottal closure instants (GCIs) and glottal opening instant (GOIs) from electroglottographic (EGG) signals using the center frequencies of the VMD modes is also possible (Lal et al. (2018)). EWT on the other hand combines the benefits of wavelet transform and EMD. The idea behind EWT is to create BCI is a closed-loop system with feedback as one important component. Dependent on the BCI application, either to establish communication in patients with severe motor paralysis, to control neuro-prosthesis or to perform neurofeedback, information is visually fed back to the user about success or failure of the intended act. One way to realize feedback is the use of Virtual Reality (VR). Leeb et al., [27] gave an overview of BCI-based control of VR. In addition, four examples are reported in more detail about navigating in virtual environments with a cue-based (synchronous) and an uncued (asynchronous) BCI. Similar results in different virtual worlds with different types of motor imageries could be achieved, but no significant differences in the BCI classification accuracy were observed between VR and non-VR feedback. Nevertheless, the use of VR stimulated the subject's task performances and provided motivation. Recently, blood flow–based neuro imaging methods, such as fMRI and Functional Near-Infrared Spectroscopy (FNIRS), have been explored in BCI context. After reviewing recent literature on the development of especially hemodynamically based BCIs, Sorger, B., et al., [29] introduced a highly reliable and easy-to-apply communication procedure that enables untrained participants to motor independently and relatively effortlessly answer multiple-choice questions based on intentionally generated single-trial fMRI signals that can be decoded online. The proposed technique takes advantage of the participants' capability to voluntarily influence certain spatio-temporal aspects of the Blood Oxygenation Level–Dependent (BOLD) signal: source location (by using different mental tasks), signal onset and offset. It showed that healthy participants are capable of hemo-dynamically encoding at least four distinct information units on a singletrial level without extensive pre-training and with little effort. Moreover, real-time data analysis based on simple multi-filter correlations allowed for automated answer decoding with a high accuracy (94.9%) demonstrating the robustness of the presented method. Following the 'proof of concept', the next step would 23 involve clinical trials with LIS patients, undertaken in close collaboration with their relatives and caretakers in order to elaborate individually tailored communication protocols.

III. METHODOLOGY

3.1 DATASET

The IV A dataset used in the BCI competition provided by Intelligent Data Analysis Group is used as dataset for experimentation [77]. This data set consists of recordings from five healthy subjects who sat in a chair with arms resting on armrests. Visual cues indicated for 3.5 s which of the following 3 motor imageries the subject should perform: (L) left hand, (R) right hand, (F) right foot. The presentation of target cues was intermittent by periods of random length, 1.75 to 2.25 s, in which the subject could relax. Given are continuous signals of 118 EEG channels and markers that indicate the time points of 280 cues for each of the 5 subjects (aa, al, av, aw, ay). Subject aa was used in our study. Labview was used to implement the Hilbert Transform for feature extraction. The maximum and minimum energy are computed for all the evoked responses. The frequency domain of a single channel for motor evoked imagery of 'hand' and 'foot' is shown in figure 2. SVM is used to train the features.

3.2. FAST HILBERT TRANSFORM

Hilbert transforms play an important role in signal processing. Analytic signal, bandpass sampling, minimum phase networks and spectral analysis are based on Hilbert transform relationships. The obtained frequencies using Hilbert transform contain artifacts which are removed using a band pass Chebyshev filter [113] such that all frequencies below 5 Hz and above 20Hz are eliminated. The Chebyshev response achieves a faster roll-off by allowing the ripple in the frequency response. Generally, a ripple depth of between 0.1 dB and 3 dB is chosen. When the ripple is set at 0%, it is called maximally flat or Butterworth filter.

The transformation of raw EEG signals to a more appropriate pattern is an essential and indispensable part of signal processing. Different feature extraction techniques focus on various aspects of the signal characteristics. These include the power of the frequency bands, information of the existing frequency components or time-frequency variation over time values, and so forth. Based on the problem requirement, the signal engineer employs a suitable feature extraction technique. The EEG signals are non-stationary, that is, varying with time. Therefore, any feature extraction technique which extracts both the time domain and the frequency domain information is intuitively most promising. Again, the signal segment where the exact discriminating information resides is not fixed for all the subjects. Even it may vary for different trials of the same subject. So, the extraction of the Region of Interest (a segment of the original signal) becomes profoundly important for signal classification. There is a trade-off between the number of features extracted from a signal segment and the number of such segments. More features do not necessarily guarantee good classification accuracy. But if the features are extracted from the correct region of activities, it generates higher performance. These observations suggest that researchers should either develop new feature extraction techniques or propose new schemes for suitable extraction of features. Few well performing feature extraction techniques are given in Table 3.1 based on classification accuracies. We aim to develop a suitable feature extraction technique that can increase the accuracy of classification of the motor imagery EEG signal.

The missing values, unbalanced datasets, small training samples, redundant features, and nonseparable (overlapping) training data are some of the prominent reasons for poor classification accuracies. It is always encouraged to use appropriately preprocessed dataset before it feeds into any classifier. But the nature of the dataset is not always in the hand of the machine learning engineer. Therefore, exploring a classifier, less prone to the outliers, and having the ability to handle most of the said disadvantages in its favor needs to be encouraged. Each classifier has its merits and demerits. If a classifier includes properties of multiple type learners, thus, it can embrace the advantages of all and dilute the disadvantages due to the combined decision. The EEG signal classification requires high accuracy due to its life-critical nature of the application. Few best performing classification techniques are given in Table 3.2 based on their performances. One of the goals of this thesis is to identify or design a classifier that gives high accuracy on the standard BCI datasets.

High dimensional feature-space incurs computational overhead in classification. Moreover, the use of all the features does not necessarily assure the best classification accuracy. If some of the features are highly correlated with one another or have minimal discriminatory contribution in the classification model, then it is efficient to select the best discriminating features from the original feature-set. Feature selection is not only apt for reducing the feature-set length but also increases the accuracy by discarding redundant non-discriminatory features. Currently, very few such approaches have been implemented on the motor-imagery EEG signal classification. It has huge potential in this domain as real-time BCI applications require lightweight prediction model

3.3.PREPROCESSING

The dataset contains raw EEG signals for three EEG electrodes C3, Cz and C4. As it is stated in Section 1.1.4, left-hand and right-hand movements are dominantly related to the brain regions tapped by the C3 and C4 electrodes. The region of our interest in each EEG signal starts at t = 3 seconds, lasts for 6 seconds and ends at t = 9 seconds. The IEEE 10−20 electrode placement and the signal description are shown in the Figures 4.1 and 4.2. This dataset does not have any major artifacts. However, the raw EEG signal is filtered with an elliptic band-pass filter using the cut-off frequencies 0.5 Hz and 50 Hz at a sampling rate of 128 Hz.

3.4. BLOCK DIAGRAM

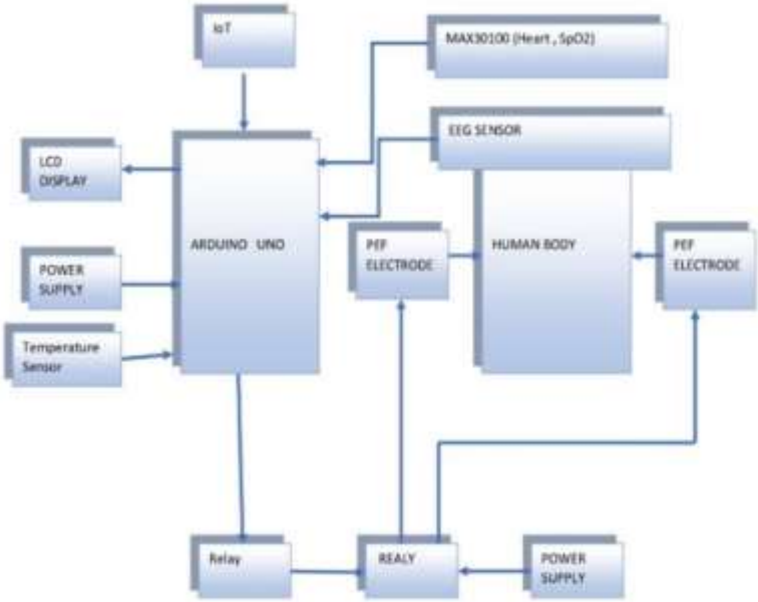

Fig1.Block diagram

IV.IMPLEMENTATION AND RESULT

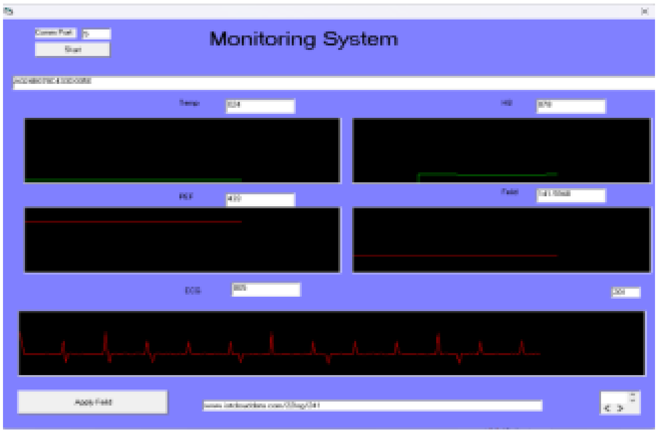

Fig2.Monitoring System

The proposed system monitors the heartbeat of the Human and temperature and humidity of the surrounding. Temperature monitoring is done in order to keep the environment suitable. It produces Pulse electric field (PEF) to the field and using to sense the electro encephalography (EEG).The monitored values are stored in Wifi-IOT logs

Fig 3. WIFI-IOT logs

V. CONCLUSION AND FUTURE WORK

Most BCIs are based on Electro Encephalo Graphy (EEG) as it provides a non-invasive method for recording the electrical fields directly produced by neuronal synaptic activity. The EEG signal is recorded from scalp electrodes by a differential amplifier in order to increase the Signal-to-Noise Ratio of the electrical signal that is attenuated by the skull. This signal is continuously sampled (typically 128 Hz - 512 Hz) to provide a high temporal resolution, making EEG an ideal method for capturing the rapid, millisecond-scale dynamics of brain information processing with a simple setup. In this chapter, a novel method of feature extraction was proposed by converting the time series EEG data to frequency domain using Hilbert Transform for BCI system. Results show that the classification accuracy of SVM-RBF kernel is obtained as better accuracy than other classifiers. Performance of SVM-RBF kernel is better by 3.63% than SVMLinear kernel, by 1.44% than SVM Poly kernel, by 11.32% than Naïve Bayes and by 13.74% than KNN. Similarly, recall and precision for SVM-RBF kernel performs better than other classifiers.In this work, it was proposed to extract features from EEG data by converting the time series EEG data to frequency domain using Hilbert Transform and PCA for feature reduction. The pre-processed signal is classified using Multilayer Perceptron using sigmoid and tanh function. Experiments are conducted using tenfold cross validation and different learning rates and momentum. The accuracy obtained is comparable with the results obtained from other researchers in literature.

The proposed method is extremely fast in both feature extraction and classification. The classification accuracy of SVM-RBF 149 kernel achieves better for feature selection PSO. Among overall comparison, PSO performs better than IG. Results with PSO show that the classification accuracy of SVM-RBF kernel achieves better by 4.22% than SVM-Linear kernel, by 0.69% than SVM Poly kernel, by 7.89% than Naïve Bayes and by 10.91% than KNN. Similarly, recall and precision for SVM-RBF kernel for feature selection PSO perform better than other classifiers. Also convergence occurs at iteration = 200 itself and so 81 features have been selected from this process.

In this study, classifiers such as Hybrid PSO-MLPNN and Hybrid PSOLVQNN are considered for measuring classification accuracy, recall and precision. Results show that the classification accuracy of Hybrid PSO MLPNN performs better than Hybrid PSO LVQNN by 2.03%. Similarly, recall and precision for of Hybrid PSO MLPNN perform better than other classifiers.

In this study, classifiers such as PSO-MLPNN, Hybrid PSO MLPNN, PSOMLPNN-PSO based weight optimization, Hybrid PSO-MLPNN- PSO based weight optimization, PSO-MLPNN-Hybrid PSO based weight optimization and Hybrid PSO-MLPNN-Hybrid PSO based weight optimization are used for measuring classification accuracy, recall and precision. Results show that the classification accuracy of Hybrid PSO-MLPNN-Hybrid PSO based weight optimization performs better than other techniques. Results show that the classification accuracy of Hybrid PSO-MLPNN-Hybrid PSO based weight optimization performs better by 6.58% than PSO-MLPNN, by 4.55% than Hybrid PSO MLPNN, by than PSO-MLPNN-PSO based weight optimization, by 150 1.92% than Hybrid PSO-MLPNN- PSO based weight optimization and by 2.58% than PSO-MLPNN-Hybrid PSO based weight optimization. Similarly, recall and precision for of Hybrid PSO-MLPNN-Hybrid PSO based weight optimization perform better than other classifiers. Also, while measuring the best fitness,the convergence occurred at iteration 170 for PSO and at iteration 160 for Hybrid PSO. Hence Hybrid PSO performs better than PSO by 10.13%.

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