Original Article

Thought-Actuated Wheelchair Navigation with Communication Assistance Using Statistical Cross-Correlation-Based Features and Extreme Learning Machine

Abstract

Background: A simple data collection approach based on electroencephalogram (EEG) measurements has been proposed in this study to implement a brain–computer interface, i.e., thought-controlled wheelchair navigation system with communication assistance. **Method:** The EEG signals are recorded for seven simple tasks using the designed data acquisition procedure. These seven tasks are conceivably used to control wheelchair movement and interact with others using any odd-ball paradigm. The proposed system records EEG signals from 10 individuals at eight-channel locations, during which the individual executes seven different mental tasks. The acquired brainwave patterns have been processed to eliminate noise, including artifacts and powerline noise, and are then partitioned into six different frequency bands. The proposed cross-correlation procedure then employs the segmented frequency bands from each channel to extract features. The cross-correlation procedure was used to obtain the coefficients in the frequency domain from consecutive frame samples. Then, the statistical measures ("minimum," "mean," "maximum," and "standard deviation") were derived from the cross-correlated signals. Finally, the extracted feature sets were validated through online sequential-extreme learning machine algorithm. **Results and Conclusion:** The results of the classification networks were compared with each set of features, and the results indicated that μ (*r*) feature set based on cross-correlation signals had the best performance with a recognition rate of 91.93%.

Keywords: *Brain–computer interface, communication assistance, online sequential-extreme learning machine, statistical cross correlation-based features, wheelchair navigation system*

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Introduction

The fundamental needs of people in day-to-day routine involve walking and interacting with other individuals. Individuals with specific disabilities, including motor neuron disease, severe spinal injuries, involuntary speech failure, and brainstem stroke, have limited mobility and interaction with each other (loss of muscle coordination and speech). Such individuals have active brain functions, and are often referred to as differentially disabled (DE).[1,2] Under these conditions, DE patients have a hard time to walk or communicate with the outside world. It is, therefore, important to provide the DE communities with an assistive technology device (ATD), enabling them to lead their healthy and normal lives. To date, various ATDs have been established using bioamplifiers, for example, cursor movement,[3] neuroprosthetic arm,[4] whole-body movement,[5] emotion recognition,[6] and driver sleepiness detection,[7] motivated by the transmission of noninvasive brain function measurements through effective electroencephalogram (EEG) amplifiers.[8,9] This study currently intended in recognizing unspoken speech signals and controlling wheelchair mobility without voluntary muscle function.[10-16]

With regard to the BCIs for speech communication system,[17] a BCI was proposed that can recognize seven words using electrical and magnetic brain waves, acquired under three experimental conditions (electromyography [EMG] results, single-trial predictions, and subject-independent predictions). It is emphasized from the research that

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brainwaves contain significant information about the mentally processed words and therefore, it is possible to recognize thought-controlled words using signal processing algorithms.[18] Researchers carried out experiments using five locked-in patients based on slow cortical potentials (SCPs), self-regulated as a control signal to choose alphabet (ABCs), words, or pattern symbols in a computer-based language support arrangement. From this analysis, it is observed that adequate learning speed and success rate are necessary for SCP-based experiments when transmitting binary decisions to the computer. Porbadnigk *et al*., 2009, introduced a BCI including a brief representation of the double-tree complex wavelet transform and linear discriminant analysis (LDA) paradigm for speech production.[19] The developed model can recognize five words using a 16-channel EEG data acquisition system, but this methodology is still not established in practice and has a low performance rate of 45.50% percent. Guenther *et al*., 2011, proposed a practical implementation and development of assistive BCI with real-time speech synthesis; the developed system uses the formant tuning analysis and a Kalman filter (linear Gaussian model) to drive a speech synthesizer.[20] Particularly, this approach has been used to recognize vowel productions in a customized mode (subject independent). The electrodes were implanted using MRI-guided stereotactic surgery, and the results suggest that the average performance rate hits 40%–70% and the information transfer rate (ITR) is within 50 ms, across sessions. Salama *et al*.[21] indicated that the classification rate for unspoken speech recognition relies on the concentration of the individual on the task and captured signal with less artifacts. The findings were based on the acquisition of a single brainwave electrode channel to distinguish two Arabic words "YES" and "NO."

With regard to the BCIs for navigating an electric wheelchair, Tanaka *et al*., 2005, used twelve-channel EEG acquisition system to acquire brain signals using motor imaginary tasks (LEFT or RIGHT).[22] The results suggest that subject-independent analysis based on recursive training algorithm shows an average classification rate of 80%. Müller-Putz *et al*., 2008, and Pfurtscheller, 2008, have shown that a tetraplegic individual can use brain waves to direct wheelchair trajectory in virtual reality using the interpretation of DE footstep motions.[4,23] The proposed system based on a patient with single-channel analysis has an average performance rate of 90% and single runs up to 100% using asynchronous tasks. Leeb *et al*., 2007, presented an experiment based on two individuals in five different experimental sessions using imaginary tasks and a simulated wheelchair.[24] Based on the experiments, the machine has a reliable user-defined EEG feature that improves the recognition of imaginary motor activity. From the analysis, individual 1 was able to control the wheelchair with an average of 80% success rate, and the individual can control the dynamic robots autonomously over prolonged periods without the use of sophisticated evolutionary algorithms. A research work proposed by[10] introduced a four-tactile stimulator BCI that helped participants maneuver through the stimuli shown in the odd-ball paradigm. The suggested procedure can also be used to control the movement of wheelchairs and recognition of speech. The results of the outcomes were evaluated by the individuals who controlled the virtual wheelchair. A recent review by[25] stated that the use of P300, sensory motor rhythms (SMRs), or steady-state visual-evoked potential (VEP) in most BCIs has shown promising results, but has been focused on offline evaluation of the acquired signals (database). BCIs are under investigation for real-time implementation with actual online testing of new feature extraction algorithms and classifiers. It is, therefore, important to use enhanced EEG recording technologies, optimized signal analysis algorithms, and real-time integration with online evaluation for effective interaction between the user and the BCI.

Lawhern *et al*., 2018, proposed a compact EEG-based BCI, i.e., EEGNet, using convolutional neural network.[26] The proposed network model was evaluated across four BCI paradigms: P300 visual-evoked potentials, error-related negativity response, movement-related cortical potentials, and SMR. Research findings suggest that particular EEGNet establishes a reliable framework for learning an extensive range of intelligible characteristics across a variety of BCI tasks.

From literature, it can be observed that despite the discussed articles, there is no research addressed with the extended use of BCI technologies enabling both mobility and speech communication using a custom brain activity measurement approach. Moreover, EEG-based navigation and communication technologies have shown that the efficiency of an efficient BCI is largely contingent on the tasks being executed, the number of EEG channels (electrode positions) being used, and the procedure used for data acquisition. It is also observed that BCI's classification performance or ITR differs with different paradigms (SCPs, P300, YES/NO, and cursor movement), individuals (normal or differentially enabled), and process (custom or generalized mode). The possible way to achieve a successful BCI is by choosing proper data acquisition tasks, stimuli (thought-evoked potential [TEP] or VEP), robust signal processing algorithms, and using suitable training for real-time implementation in different circumstances.[10,13,17,21,22,26-30]

It is also known that certain aspects are important and need to be explored in order to potentially develop wheelchair navigation system (WNS) with communication assistance, for example, backpropagation-based multi-layer neural network, hidden Markov modes, support vector machine (SVM), Gaussian mixture models, and LDA are the most efficient and widely used algorithms for classifying motor imagery tasks, despite the mean square error and number of training iterations can be optimized.[19,31-33] In addition, training time for participants to enhance their expertise and effective integration with reliable features has been considered for real-time implementation.[16,24] As a result of the above literatures, the noninvasive BCIs have given significant contributions to the implementation of the proposed WNS system in this research as a first stage upward to the potential for speech and motor control through the proposed protocol. In the absence of muscle coordination and speech, the proposed system can be used to assist DE peoples. This research attempts to develop a wheelchair that provides mobility control and communication assistance via brainwave stimulation. The established device could then be used by DE and other speech-impaired individuals to move around and express their desires to anyone. The protocol used for data acquisition and preprocessing of the recording signals is explained in section 2. Cross-correlation-based techniques have been proposed in this analysis to derive the features from the frequency-band signals at every electrode channel.[33] As many classifiers such as backpropagation neural network,[34] SVM,[35] and LDA[36] have also shown greater efficiency in recognition, the proposed extreme learning machine (ELM) by Huang *et al*., 2012, is indeed an effective tuning-free algorithm for training a feature set that employs simply single-hidden layer in feed-forward neural network (SLFNs).[37,38] The emergence of ELM in the artificial neural nets allows reduced time for training the network models relative to the artificial neural network, which has also been employed in other areas of research, particularly in BCI.[37-39] As a result of the literature, the statistical features extracted for the WNS classification system are linked with its corresponding imagery tasks and evaluated using online sequential (OS)-ELM.[40] Section 3 explain the feature extraction method and the classifiers used in this research. Figure 1 illustrates the schematic depiction of the proposed WNS system.

Wheelchair Navigation System Database

The data acquisition process was carried out in the laboratory environment at the School of Mechatronics Engineering,

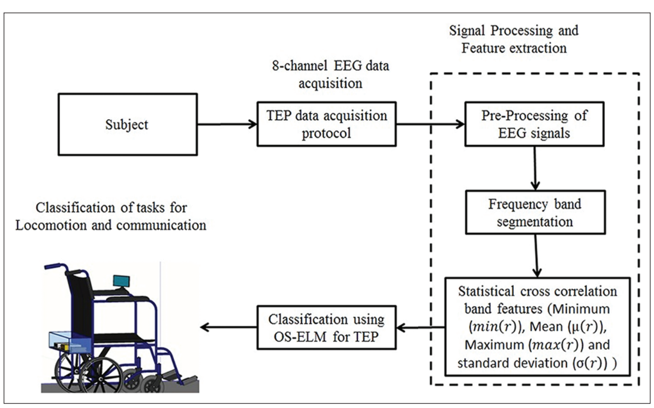

Figure 1: Schematic representation of the proposed wheelchair navigation system

University Malaysia Perlis.[41] Prior to initiating the data collection process, the experimental procedure has been registered and accepted by the "National Medical Research Registration" (NMRR ID: NMRR-13-51-14570) and received ethical clearance with Medical Research Ethics Committee (MREC) and Ministry of Health Malaysia (Ref:[7]dlm. KKM/NIHSEC/800-2/2/2Jld2P13-179).[41] The section discusses several basic techniques used for the experimental setup, including the configuration of wireless bioamplifier and positioning of electrode channels for the measurement of brain activities. In addition, appropriate task identification, the data capture process, and the development of the WNS database were also addressed. This procedure is important to classify the tasks captured based on the TEPs that control the WNS.

Experimental Setup and Data Acquisition

The experimental setup has been configured with a bio-signal data acquisition system known as "g-mobilab+" (a device that captures EEG signals from eight-channel positions) to record brainwave responses.[42] The data acquisition framework comprises the following components:

a. Electrode cap with nine individual screw-in electrodes
b. A bio-signal amplifier
c. Electrode gels, and
d. Wireless data transmission through the MATLAB® integrated programming package.

In the experimental paradigm, it is proposed to attempt and establish a BCI device suitable for DE community to operate joystick of the wheelchair and interact with anyone (through any odd-ball paradigm), based on brainwave signals.[42,43]

Therefore, three major tasks that describe the movement of the robotic wheelchair as well as the selection of isolated words/phrases in an odd-ball paradigm, for example, LEFT-, FORWARD-, and RIGHT-hand motion control, were incorporated in the data acquisition process. To communicate with the outside world and to alert the caretaker under an emergency situation, additionally, the following three tasks have also been introduced: "Help," "YES," and "NO" tasks to direct the basic human needs. In this experiment, the EEG responses obtained for the RELAX (normal) task have been used as the reference signal. The acquisition was performed in a protected semi-sound chamber, in which the individuals were seated in comfortable state and performed seven asynchronous tasks. The signals are obtained in circumstances where the individuals remain stable. There were no overt movements allowed during the 12 s data recording process.

In this process, the motor imaginary signals relating the tasks are measured from eight electrode locations: they are "temporal lobe" (T3 and T4), "central lobe" (C3 and C4), "parietal lobe" (P3 and P4), and "occipital lobe" (O1 and O2), when the individual executes the seven tasks asynchronously. Moreover, reference recording schemes have been used in the electrode positioning procedure, and the electrodes are positioned at the locations (T3 and T4, C3 and C4, P3 and P4, O1 and O2) with one specific electrode on the left ear lobe of the individual's body. The potentials were maintained relatively constant.[44,45]

The experimental WNS model measures the patterns of brain activity to distinguish the rhythmic pattern for an individual's seven different thoughts. Therefore, the brainwave signals were collected from a grid of eight Ag/AgCl scalp electrodes with a sampling rate at 256 Hz during the data acquisition procedure. The electrodes were mounted on the scalp as stated in the international 10–20 lead system.[46] The electrodes are mounted on scalp locations, and g-tec impedance checker has been used to monitor the impedance levels. In addition, the impedance level has been subsequently measured after each task was completed and kept below 10 kΩ.

Thought-Evoked Potential Data Acquisition and Wheelchair Navigation System Dataset

In the development of WNS dataset, 10 healthy naives to BCI were selected as volunteers in the data acquisition process (eight male individuals, aged between 21 and 30 years, and two female individuals aged 24 years). In the data collection of each task, a detailed demonstration on the tasks (simulation of the task) was given to the individuals through a liquid crystal display (LCD) monitor. The simulation provides a detailed demonstration of the movement of wheelchair joystick for LEFT, FORWARD, and RIGHT directions using the right hand, both hand, and left hand movement. The visual shows a volunteer executing up-down and left-right head movements with tasks involving "YES" and "NO." For "HELP," the individual was instructed to mentally pronounce the term "HELP" (how he/she normally call for help in an emergency), rather than contemplating the hand movements. The LCD screen is then switched off, and a 2-s blank screen was displayed, while, as shown on the simulation, the participant has been asked to perform the tasks asynchronously. The participant subsequently performs a given task, and the EEG responses were collected across the parietal lobe (P3 and P4), temporal lobe (T3 and T4), central lobe (C3 and C4), and occipital lobe (O1 and O2) locations for 12 s. According to the 10–20 method, ground and reference electrodes were placed in Fpz and left earlobe location.[47]

At a frequency of 50 Hz, the acquired EEG signal has interference of unknown noise characteristics such as power line disruption. Hence, a simple 1st-order IIR notch filter has been designed to remove power line disruption from signals acquired. Filter center-frequency (F0) was approximately selected around 50 Hz with bandwidth of $\Delta F = 4$ Hz.[46,48] The recorded signals were subsequently quantified into discrete signals using a sampling frequency of 256 Hz. Similarly, ten trials were made for each task during the acquisition process, and the participants were allowed to take breaks between each task for 10 min. Additionally, for ten participants, this process has been continued, and the captured signals are established in this manner and labeled as the WNS dataset. The WNS dataset comprises $10_{\text{participants}} \times 7_{\text{tasks}} \times 10_{\text{trials}}$. The proposed TEP-protocol-based WNS database will also be established for future research using more volunteers to develop the generalized system. The database was then used for validation using hypothesis testing based on analysis of variance algorithm, and P value was found to be below α (significance level: 0.05).[49]

Statistical Cross-Correlation Based Features

Frame Blocking and Frequency band Extraction

The eight-channel raw EEG signals were processed to 10-s signal in the feature extraction procedure by excluding one second at the beginning and end of the signal to eliminate the noise due to electrical inference (amplifier ON/OFF). The segmented signals are also categorized into frames of equal length (2 s with 512 samples/frame) including an overlap (1 s with 256 samples).

The first frame is, therefore, composed of 512 samples. Following an overlap of $m - 1$ (256 samples), the second frame was initiated to overlap the second frame with the $n - m$ samples of the first frame. This process was performed in the frame segmentation procedure until all EEG signals were used as an input signal to derive the frequency band.[50]

The frequencies above 100 Hz have very little information about the tasks performed on the basis of the TEP protocol;[46,51] therefore, the segmented frame signals are used with band-pass filters to remove artifacts and EMGs above 100 Hz and below 0.5 Hz. The segmented frame signals are split into the following six specific bands: delta-band (δ), 0.1–4 Hz; theta-band (θ), 4–8 Hz; alpha-band (α), 8–16 Hz; beta-band (β), 16–32 Hz; gamma 1-band ($\gamma 1$), 32–64 Hz; and gamma 2-band ($\gamma 2$), 64–100 Hz. The frequency band is implemented over each frame signal segmented from the eight different channels, and the features are derived using the statistical cross-correlations (SCC) algorithm.

Statistical Cross-Correlations Based Features

Cross-corr (r) analyses were used in this article to examine the segmented signals recorded based on the TEP procedure. r is a form of template-matching tool among two input sequences, which is especially prominent in identifying the significant differences across the active potentials of the neuron.[52,53] Considering r is a successful method for extracting the features in BCI studies, which also offers high-efficiency level even when the signals are effected by slight variations in the location of the electrodes,[33,52] This methodology was implemented in this analysis to determine the interrelationship between the corresponding sets.

A simple Hamming window has been placed across each frame in the feature extraction process, and the Fast Fourier Transform Algorithm (FFT) algorithm was implemented to extract the frequency components from the time domain sequence.[54] Accordingly, the six frequency band signals (δ, θ, α, β, $\gamma 1$, and $\gamma 2$) were extracted using Welch's band-pass filters for each frame.[50] In addition, for all channels, the FFT frequencies are cross-correlated among i^{th} and the $(i + 1)^{th}$ frames to determine the interrelationship between the two discrete frames. Hence, the cross-correlation sequence $r^{j}_{(\delta i,\delta i+1)}$ for was determined one by one from δi band frequencies and the $\delta + 1$ band frequencies.

where

i represents the frame index

j represents electrode channel index.

Then, the procedure is repeated to compute the cross-correlation sequence for $r^{j}_{(\theta i,\theta i+1)}$, $r^{j}_{(\alpha i,\alpha i+1)}$, $r^{j}_{(\beta i,\beta i+1)}$, $r^{j}_{(\gamma 1i,\gamma 1i+1)}$, and $r^{j}_{(\gamma 2i,\gamma 2i+1)}$. In addition, the cross-correlated samples are used to derive four distinct statistical measures which are minimum (min [r]), mean (μ [r]), maximum (max [r]), and standard deviation (σ [r]). These corresponding feature samples are configured to interpret the r sequence distribution and minimize the dimensions of the set of features.[33] For eight channels, as a result, 48 features (6 frequency bands × 8 channels) were obtained between each set of frames. Similarly, for each task, features were extracted at each trial, and the resulting set of features comprises 6300 samples (10 participants × 10 trials × 9 frames × 7 tasks). In similar fashion, the features were derived from each task across every trial to construct the feature set. Consequently, the feature set composed of 6300 samples (10 participants × 10 trials × 9 frames × 7 tasks) is developed. The set of features are then used to design the architecture of the classifier and to recognize the tasks.

$$min(r)^{i,j} = \begin{Bmatrix} minr^{j}_{\delta i,\delta i,+1}, minr^{j}_{\theta i,\theta i+1}, minr^{j}_{\alpha i,\alpha i+1}, \\ minr^{j}_{\beta i,\beta i+1}, minr^{j}_{\gamma 1i,\gamma 1i+1}, minr^{j}_{\gamma 2i,\gamma 2i+1} \end{Bmatrix} \quad (1)$$

$$\mu(r)^{i,j} = \begin{Bmatrix} \mu r^{j}_{\delta i,\delta i,+1}, \mu r^{j}_{\theta i,\theta i+1}, \mu r^{j}_{\alpha i,\alpha i+1}, \\ \mu r^{j}_{\beta i,\beta i+1}, \mu r^{j}_{\gamma 1i,\gamma 1i+1}, \mu r^{j}_{\gamma 2i,\gamma 2i+1} \end{Bmatrix} \quad (2)$$

$$max(r)^{i,j} = \begin{Bmatrix} maxr^{j}_{\delta i,\delta i,+1}, maxr^{j}_{\theta i,\theta i+1}, maxr^{j}_{\alpha i,\alpha i+1}, \\ maxr^{j}_{\beta i,\beta i+1}, maxr^{j}_{\gamma 1i,\gamma 1i+1}, maxr^{j}_{\gamma 2i,\gamma 2i+1} \end{Bmatrix} \quad (3)$$

$$\sigma(r)^{i,j} = \begin{Bmatrix} \sigma r^{j}_{\delta i,\delta i,+1}, \sigma r^{j}_{\theta i,\theta i+1}, \sigma r^{j}_{\alpha i,\alpha i+1}, \\ \sigma r^{j}_{\beta i,\beta i+1}, \sigma r^{j}_{\gamma 1i,\gamma 1i+1}, \sigma r^{j}_{\gamma 2i,\gamma 2i+1} \end{Bmatrix} \quad (4)$$

where *min(r)* –, μ(r) – *mean*, *max(r)* – *maximum* and *σ(r)* - standard deviation of the r sequence in the i^{th} frame of the j^{th} electrode location.

The procedures to implement the segmentation of frequency bands and cross-correlation features are illustrated in Figure 2.

Classification of Thought-Evoked Potential Tasks Using Online Sequential-Extreme Learning Machine Algorithm

ELMs are fundamentally inspired pattern recognition techniques built using SLFN that provides quick training speed, flexibility in implementation, and reduced manual interruptions (Huang, 2004).[38] The concept of ELM becoming a potentially promising technique for BCI technologies has been developed significantly over the years.[37-39] Liang *et al*.[40] introduced an effective OS-ELM, which could sequentially process feature vectors and update the existing model with the input of new samples. The SLFN algorithm can learn sequentially with "one per chunk" or "one by one chunk," which has a set or different chunk size.[40] OS-ELM comprises of two different stages: a first stage and a secondary learning process. Therefore, with the OS-ELM algorithm used in this study,[55] the statistical features derived from the cross-correlation analysis were evaluated.

In this analysis, a simple WNS model has been implemented employing OS-ELM for multiclass pattern recognition. The set of features based on every statistical measure is then processed and linked with the tasks (6300 × 48 features). In addition, the feature vectors are normalized using the bipolar normalization approach, which can be seen in Eq. 5, in which the dataset was transformed between − 0.9 and 0.9 (Sivanandam, 2009).[56] The feature set has been portioned into training and testing sets based on 5-fold cross-validation method[57] for each feature set (min [r]), μ(r), max(*r*), and σ (r). The training set has 5040 × 48 samples (80% master data set) as well as the test set does have the other 1260 × 48 samples (20% master data set) to recognize the TEP tasks.[58] In this analysis, 48 neurons in the input layer, and 7 neurons in

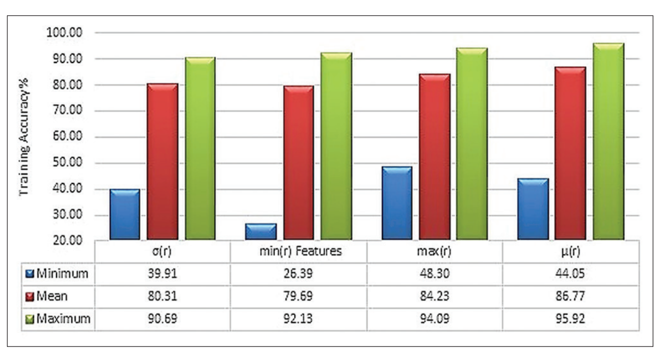

Figure 2: A flowchart procedure for the segmentation of frequency bands and cross-correlation feature

the output layer, were formed in OS-ELM architectures. We know that the hyperbolic sigmoidal (tanh) activation feature transforms every value into the −0.9 to 0.9 range. Tanh activation, as shown in Eq. 6, has been used in the configured OS-ELM architectures to activate output layers. To improve performance, the hidden neurons were increased linearly between 30 and 1400 neurons. Eventually, the architecture was trained for ten tests with each feature. The primary hidden neuron has been configured to be equivalent toward the samples in the training data. Figure 3 shows the developed architecture's average training and testing performance across ten trials with varying hidden neurons.

The maximum number of hidden neurons, i.e., 1400, was chosen based on the highest classification rate. The performance rate has increased substantially as hidden neurons hit 1400 neurons.

$$S_{ij} = \frac{1-e^{-(ij)}}{1+e^{-(ij)}} \quad (5)$$

S_{ij} is normalized input sample of the i^{th} row and j^{th} column,

$$G(ij) = \tanh(ij) = \frac{e^{ij} - e^{-ij}}{e^{ij} + e^{-ij}} \quad (6)$$

G_{ij} is normalized output sample of the i^{th} row and j^{th} column.

For each subset, OS-ELM architectures were trained for ten trial weights. With the initial subset, the neural architecture has been supervised with 8/10 set of features, and the level of recognition was measured with the remaining feature sets ('2/10' subset). Kohavi, 1995, proposed a cross-validation method for evaluating the classifiers developed from different sets of derived features.[58] Therefore, the developed classifiers in this experiment were validated with each '2/10' feature subset for 10 different trials. Table 1 illustrates the performance of the OS-ELM classifier models based on the 5-fold cross validation approach with time taken during training (seconds), time taken during testing (seconds), training accuracy (%), and test accuracy (%).

Results and Discussion

This work preprocesses and blocks raw EEG signals into multiple frame samples. Then, the frame samples are used to extract the *δ, θ, α, β, γ1, and γ2* band frequencies. The statistical features are obtained through the correlation among two sequential frequency band frames, and the features are linked to a specific TEP task. The features derived are characterized with OS-ELM algorithm. The statistical analysis of *r* features and the recognition rate of the system implementations are presented in Table 1. Figures 4 and 5 indicate the generalized training time and recognition accuracy attained through the training and evaluation of feature sets.

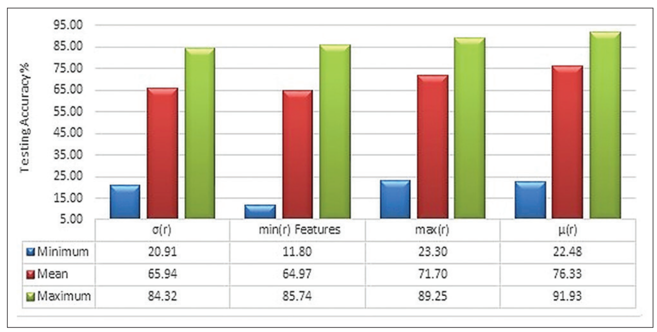

Figure 3: Comparison of training and testing accuracy executed during the training of online sequential-extreme learning machine algorithm models

Table 1: Comparison of wheelchair navigation system classification using statistical features and online sequential-extreme learning machine algorithm

Statistical features of cross-correlation	Comparison of WNS classification using OS-ELM and statistical features		
	Training time (min)	Training accuracy (%)	Testing accuracy (%)
σ (*r*)			
Minimum	60	39.91	20.91
Mean	2950	80.31	65.94
Maximum	10,940	90.69	84.32
Minimum (*r*)			
Minimum	30	26.39	11.80
Mean	3320	79.69	64.97
Maximum	14,210	92.13	85.74
Maximum (*r*)			
Minimum	140	48.30	23.30
Mean	4530	84.23	71.70
Maximum	20,890	94.09	89.25
μ (*r*)			
Minimum	80	44.05	22.48
Mean	6220	86.77	76.33
Maximum	36,610	95.92	91.93

WNS – Wheelchair navigation system; OS-ELM – Online sequential-extreme learning machine algorithm

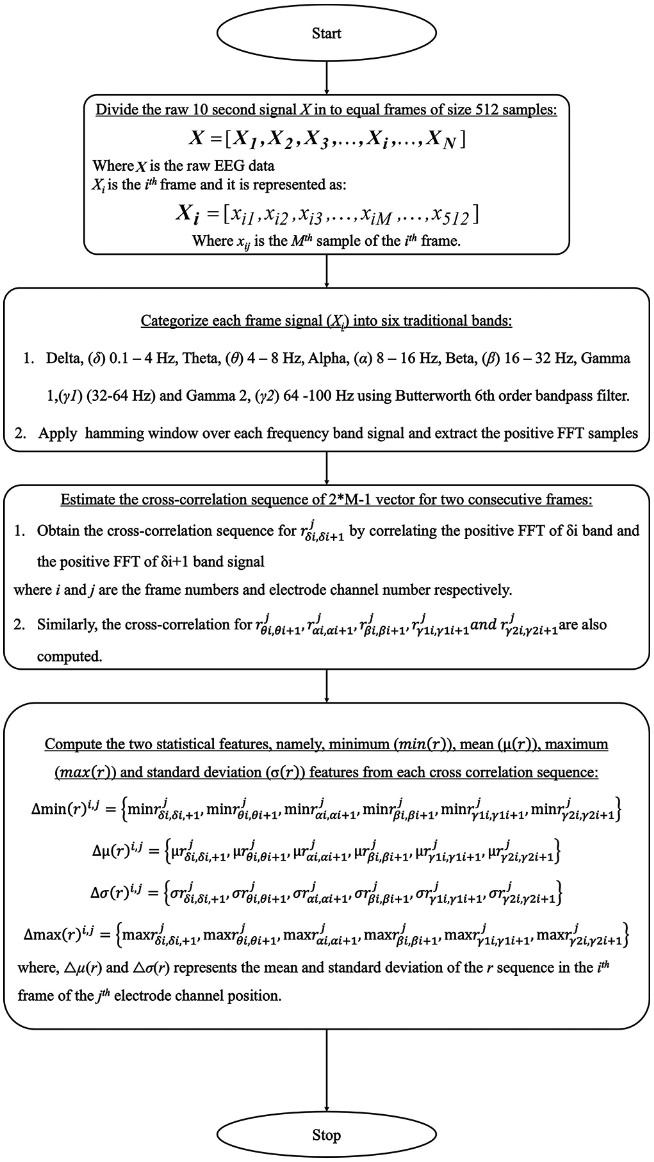

Figure 4: Overall training accuracy obtained during training and testing the feature sets

From Figure 4, it can be emphasized that the statistical features of the OS-ELM model reach the minimal training performance (average) σ(*r*) – 39.91%, min(*r*) – 26.39%, max(*r*) – 48.30%, and μ(*r*) – 44.05%. It can also be emphasized that the classifiers have obtained maximal training performance (average) of σ(*r*) – 90.69%, min(*r*) – 92.13%, max(*r*) – 94.09%, and μ(*r*) – 95.92%. Further, μ(*r*)-based classifier model hits the highest accuracy 95.92% (average) in recognition and σ(*r*) reaches the average lowest accuracy of 90.69% (average) in recognition.

From Figure 5, it can be emphasized that the statistical features of the OS-ELM model reach the minimal testing accuracy (average) of σ(*r*) – 20.91%, min(*r*) – 11.80%, max(*r*) – 23.30%, and μ(*r*) – 22.48% and the maximal testing accuracy (average) of σ(*r*) – 84.32%, min(*r*) – 85.74%, max(*r*) – 89.25%, and μ(*r*) – 91.93%.

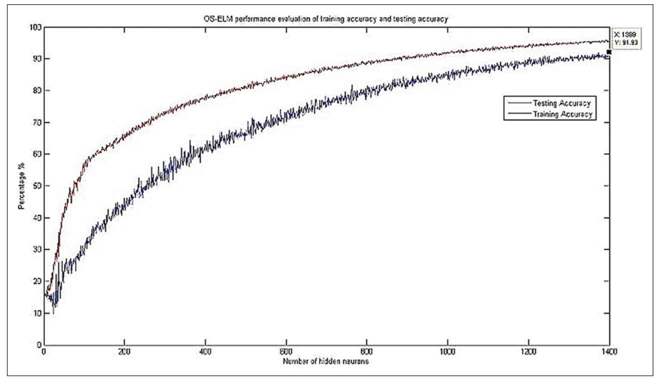

Figure 5: Overall testing accuracy obtained during training and testing the feature sets

It can be interpreted that the μ(*r*) reaches the highest accuracy of 91.92% (average) in recognition, and σ(*r*) hits the lowest accuracy of 84.32% (average) in recognition. Figures 3 and 6 similarly represent a comparison between training and testing performance conducted throughout the OS-ELM modeling and the total overall training time attained throughout OS-ELM training employing μ(*r*).

From Figure 3, it can be emphasized that the highest training accuracy of 95.92% and the highest testing accuracy of 91.93% have been attained, while the network was trained with 1399 hidden neurons. As shown in Figure 3, the network's performance has increased gradually by raising the hidden neurons linearly. The analysis suggests that the feature set has a robust classification system, based on OS-ELM learning.

From Table 1, it can be emphasized that the statistical features of the OS-ELM model reach the lowest training time (average) for σ(*r*) – 60 ms, min(*r*) – 30 ms, max(*r*) – 140 ms, and μ(*r*) – 80 ms and the highest testing time (average) of σ(*r*) – 10,940 ms, min(*r*) – 14,210 ms, max(*r*) – 20,890 ms, and μ(*r*) – 36,610 ms. It is also emphasized that the μ(*r*) reaches the maximal training time of 36,610 ms (average) and σ(*r*) reaches the lowest training time of 60 ms (average).

Confusion Matrix for the Classification of Seven Tasks

The confusion matrix is a visual interface method, which provides the classifier's actual output and predictions. The OS-ELM confusion matrix has the maximal recognition rate of 91.93% using μ(*r*) features, as shown in Table 2. From Table 2, it can be emphasized that perhaps the "LEFT" task has the lowest recognition rate of 89.53% and the "HELP" task has the highest recognition rate of 95.81%. It can be also emphasized that perhaps the "RELAX" task has the lowest false recognition rate of 41.18% (7 samples/17 samples) and the "RIGHT" task has the highest false recognition rate of 76.47% (13 samples/17 samples). In addition, the overall accuracy of the total number of correct predictions achieved for the proposed model is 91.94%. The results from the analysis illustrate that investigation on WNS with the

Table 2: Confusion matrix for maximum classification accuracy of 91.93% using μ(*r*) feature set and online sequential-extreme learning machine algorithm classifier

Confusion matrix for the generalized classification system using mean feature set								
Tasks	**Left**	**Forward**	**Right**	**Help**	**Yes**	**No**	**Relax**	**Accuracy (%)**
Left	171	1	1	0	0	1	1	89.53
Forward	2	180	3	0	1	1	0	94.24
Right	0	1	174	2	1	1	2	91.1
Help	1	4	2	183	5	2	2	95.81
Yes	2	0	3	0	173	3	1	90.58
No	1	0	2	0	1	174	1	91.1
Relax	3	1	2	2	0	1	177	91.24
Miss classification rate of unclassified samples (%)	45	63.64	76.47	50	44.44	52.94	41.18	
Number of misclassifications		57		Minimum (%)				89.53
Number of unclassified samples		108		Mean (%)				91.1
Misclassification (%)		52.78		Maximum (%)				95.81

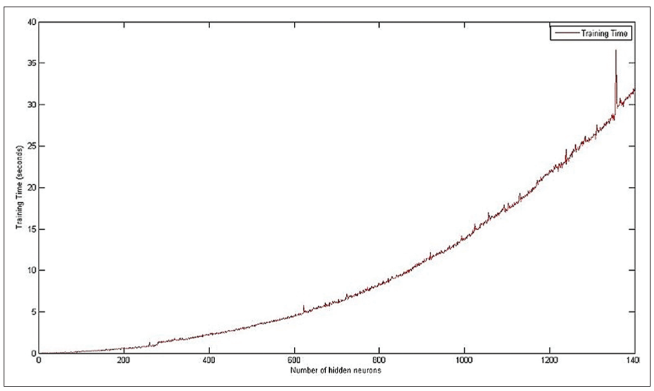

Figure 6: The mean maximum training time obtained during the training of online sequential-extreme learning machine algorithm using μ(*r*)

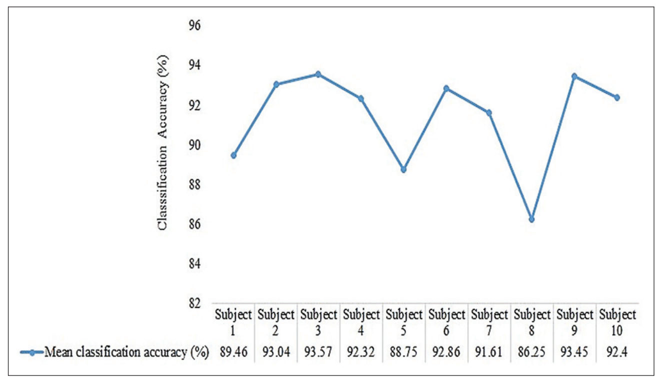

Figure 7: The comparison of mean classification accuracy, using μ(*r*) features in customized modes

communication aid using our proposed seven tasks together with the SCC-based features have shown promising results. To validate our proposed algorithm in customized modes, the data acquired from ten normal controls were used for the classification. The proposed cross-correlation technique based on different band frequencies has been used to extract the μ(r) features from two consecutive frame samples and classified using the OS-ELM classifier. Figure 7 depicts the comparison of average classification accuracy, using μ(r) features in customized modes.

The results suggest that the average recognition rate of 92.59% has been achieved. From Figure 6, it is observed that participant 9 has the highest classification rate of 93.45% and participant 8 has the lowest classification rate of 86.25% through the customized classification system. The results from the generalized and customized classification system suggest that OS-ELM for WNS tasks reaches the least training time with a self-reliant recognition rate, when comparing the findings among other nonparametric pattern recognition methods found in literature.[10,27,28,33,59]

Conclusion

In accordance with the objectives of this analysis, a simple wheelchair navigation system with communication assistance (simulation model) has been established using cross-correlation features and OS-ELM pattern recognition algorithm. The trained OS-ELM model representing the classification system can also be used to control the wheelchair or to choose isolated words in an odd-ball paradigm for hardware implantation. The developed classification system has shown promising results for the signals obtained from normal controls, indicating explicitly that the seven tasks introduced in the protocol are convenient to memorize and execute. Therefore, it can be considered that these tasks are convenient for the DE community to grasp and perform the task to navigate the wheelchair and letter/word selection in an odd-ball paradigm. From the analyses, the results indicate a robust classification rate for the proposed feature extraction algorithm; the recognition of tasks reflects on the ability of the participant as described in Table 2, and classification performance differs with the participants as shown in Figure 6. During the training stage, the obtained results from this research indicate a minimal misclassification of 0.0454% (229/5040) samples and 0.0952% (120/1340) during the testing stage. In comparison with the study by Lawhern, 2018,[26] the researcher used the Morlet wavelet approach to analyze EEG signals (0–40 Hz). In this research, the protocol was specifically designed to elicit the tasks linked to the objectives of this research work. The EEG signals are, therefore, evaluated with the six different frequency bands, as each frequency band has meaningful information related to brain function. For the classification of WNS tasks, selection of frequency bands is, therefore, important to obtain more discriminating and dominant features.[26] The results were based on the mean and standard error of classification performance for different paradigms. In this study, the cross-correlation features extracted from two consecutive frames of each band frequencies are used for the classification based on OS-ELM pattern recognition algorithm. The overall performance of the designed classifiers was compared based on the overall training time, testing accuracy, and misclassification errors. The results are robust, and the time taken for training the network was also less for the acquired database.

This proposed study provides the DE community several potential applications and enhancements in WNS, as compared with related works such as EEG-based communication systems[17-19,21,60,61] and EEG-based navigation systems.[4,10,22,24] Also, these BCIs were developed using multi-electrode brainwave data-capturing devices (up to 16 electrodes) to recognize only two to five tasks. This can also be noted that the overall BCI recognition levels vary from 40% to 80% in the database of 5-23 subjects and patients. However, there are needs in development; in future analyses, feature extraction algorithm based on connectivity features, statistical features and power connectivity features,[62,63] deep learning algorithms, and interactive training and testing modules should be considered to enhance the recognition of tasks used in the WNS system. Finally, it is also useful to explore the useful properties of brain patterns based on the spatial and frequency domain, feature extraction algorithm, and classification techniques.

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Conflicts of interest

There are no conflicts of interest.

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