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RESEARCH ARTICLE

Brain-computer interface algorithm based on wavelet-phase stability analysis in motor imagery experiment

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Abstract

Severe movement or motor disability diseases such as amyotrophic lateral sclerosis (ALS), cerebral palsy (CB), and muscular dystrophy (MD) are types of diseases which lead to the total of function loss of body parts, usually limbs. Patient with an extreme motor impairment might suffers a locked-in state, resulting in the difficulty to perform any physical movements. These diseases are commonly being treated by a specific rehabilitation procedure with prescribed medication. However, the recovery process is time-consuming through such treatments. To overcome these issues, Brain-Computer Interface system is introduced in which one of its modalities is to translate thought via electroencephalography (EEG) signals by the user and generating desired output directly to an external artificial control device or human augmentation. Here, phase synchronization is implemented to complement the BCI system by analyzing the phase stability between two input signals. The motor imagery-based experiment involved ten healthy subjects aged from 24 to 30 years old with balanced numbers between male and female. Two aforementioned input signals are the respective reference data and the real time data were measured by using phase stability technique by indicating values range from 0 (least stable) to 1 (most stable). Prior to that, feature extraction was utilized by applying continuous wavelet transform (CWT) to quantify significant features on the basis of motor imagery experiment which are right and left imaginations. The technique was able to segregate different classes of motor imagery task based on classification accuracy. This study affirmed the approach's ability to achieve high accuracy output measurements.

Keywords: Brain-Computer Interface, electroencephalography, motor imagery, phase stability analysis, thresholding technique.

INTRODUCTION

Physical disability is among the leading cases in Malaysia [1] related with many types of diseases such as amyotrophic lateral sclerosis (ALS), muscular dystrophy (MD), and stroke which in general, it leaves patients in a locked-in state [2]. Thus, Brain-Computer Interface (BCI) is introduced in 1970s by Vidal [3,4] providing a way to connect brain to the artificial or assistive device while bypassing the channel of peripheral nerves [2,5-7]. Three common types of BCI utilized in most BCI researches which are P300 Event-Related Potential, Steady-State Visual Evoke Potential (SSVEP), and Motor Imagery (MI) [2,6,8]. While BCI can be utilized by the user as a communication tool, signal processing plays a dominant role to validate the feasibility and reliability of the entire system. Two major parts in signal processing are feature extraction and classification algorithms in which the significant features are differentiated and segregated in accordance with which classes that they should be in prior to the measurement of the performance and classification accuracy [5].

Feature extraction technique on electroencephalography (EEG) signal has been popularly utilized in BCI as done by Pichiorri *et al.* [9] in conducting stroke patient rehabilitation. Apart from that, Fourier transform are utilized in extracting features which further being used in the BCI analysis as done by Hindarto *et al.* [10], Sivakami *et al.* [11], and Wang *et al.* [12]. The signal is often quantified based on their frequency characteristics and the spectrum is estimated using Fast Fourier Transform (FFT) [12]. However, FFT-based spectral analysis requires stationarity of the analyzed signal and it is well known that EEG is a non-stationary signal. Nevertheless, the time-varying spectrum of the signal can be obtained with time-frequency representation methods such as the traditional Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Autoregressive (AR) [14].

Apart from the feature extraction, classifier also plays a major role to produce robust BCI system which will be emphasized in this research. Nowadays, ubiquitous techniques for classification of feature had been tremendously applied in most BCI projects such as support vector machine (SVM) [15,16], K-nearest neighborhood (KNN) [19,20], common spatial pattern (CSP) [15,19], and linear discriminant analysis (LDA) [20,21]. However, most of the feature classification techniques are unstable when executing output of BCI signal. SVM is one of the most common method to isolate different classes of feature (for example, right and left class of hand movement) by constructing a hyperplane between those classes [20]. Nevertheless, SVM is unable to classify every single feature which might lead to the loss of important information in a particular feature. Thus, a robust technique should be designed in order to resolve the drawbacks encountered in the aforementioned researches.

Despite the growing BCI system development in modern countries, the development of BCI-based technology is still new in Malaysia and a lot of studies need to be carried out [21]. Since the BCI system requires a very robust decision-making signal processing, there are still many methods and techniques that may be explored to develop the most efficient BCI system which provides reliable and consistent outcomes.

In this paper, an algorithm for feature extraction integrated with classification in motor imagery experiment is proposed. The first objective is to design BCI signal processing to extract and segregate the most significant features from EEG signal to be utilized in BCI system by using fourth derivatives complex Gaussian of wavelet transform. The optimization procedure is employed on the extracted features on the stage of classification of features by implementing phase synchronization stability analysis technique with the adaptation of phase-locking measurement between two input signals. In addition, the algorithms are constructed to resolve the complexity issues thereby producing a stable and time-saving system. The second objective is to evaluate the performance of the proposed technique. It is expected that the proposed technique is able to produce high classification accuracy with a robust performance on motor imagery task. The phase stability approach has been successfully performed on classifying auditory selective attention [22]. Prior to that, Savitzky-Golay filter has been utilized to produce optimal signal-to-noise ratio (SNR) and is compared to the moving-average filter at the stage of signal preprocessing.

The main contribution of this work is that a new feature classification method was proposed combining with continuous wavelet transform as a feature extraction technique. The implementation of this technique may assist researchers in classifying multiclass features especially in the field of brain-computer interface research. Evaluation of performance accuracy provides guidance in deciding the technique to be utilized in any application.

MATERIALS AND METHOD

Subject and data acquisition

ten healthy subjects (5 males, 5 females) aged between 24 and 33 years old volunteered to participate in this experiment. Below is a set of paradigms that was used as the triggering stimulus for the subject in order to be align with BCI trials for this experiment. The experimental procedure took 2 minutes and during the experiment, it is necessary to avoid any noise interference which might affect the data acquisition. As shown in the Figure 1, the subject was asked to be ready at the pre-stimulus interval and stop the task at the post-stimulus.

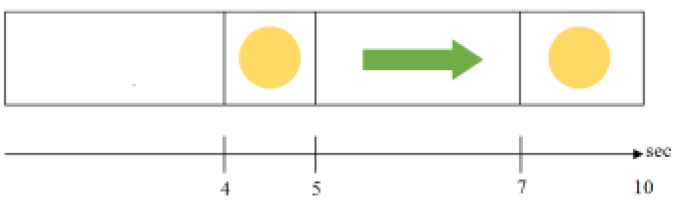


Figure 1 BCI paradigm.

Prior to the motor imagery experiment, the subject was instructed to sit on a chair while facing towards the stimulus screen at the perpendicular position with the distance of approximately 100 cm (Figure 2). Throughout the procedure, the subject was required to wear the EEG scalp. Nuprep gel was used to improve skin condition for the electrodes attachment while reducing skin impedance. Next, a set of electrodes were attached to the scalp with the adhesion of Ten20 conductive gel as it has superior adhesive to hold non-disposable of neurodiagnostic electrode surface. Three active electrodes from GTEC's company were used over the sensorimotor areas, together with a reference electrode on the right ear lobe and ground electrode on the forehead. Three electrodes used were located on C3, C4, and CZ, where most of motor planning and execution take place. The EEG signals were acquired using g.USBamp amplifier with 256Hz sample frequency.

Figure 2 Subject on experiment.

Signal preprocessing

The EEG signals are dynamic with amplitude of ±100µV without extended amplifier. However, it is usually contaminated by noise and artefact that might blur the important information. To solve this, Savitzky-Golay filter is used to denoise most of the noises underlying in EEG signals by applying linear least square method that is used to smooth the acquired EEG signals. This allows us to obtain high SNR while sustaining the original shape of the signals. The signal smoothing step applies equation 1 which was stated by Savitzky and Golay [23]. The equation consists of $n\{x_j, y_j\}$ points of $(j = 1, \dots, n)$.

$$Y_j = \sum_{i=-\frac{m-1}{2}}^{\frac{m-1}{2}} C_i y_{j+i} \tag{1}$$

where x is an independent variable and y is a dependent value. We applied the convolution set m coefficient as the value of 3-point quadratic polynomial with the set of frame length value of $n = 255$. The jth values are in a range of

$$\frac{m-1}{2} \le j \le n - \frac{m-1}{2}$$

The performance of applied filter of signals were measured by the utilization of SNR technique. SNR is measurement used in engineering and science as to obtain the desired signal to the background noises. It can be defined as

$$SNR = \frac{P_{signal}}{P_{noise}} \tag{2}$$

where P_{signal} is the power of the significant signal and P_{noise} is the power of noise signal.

Segmentation

The significant filtered data were further processed by segmentation. In this process, the data were cut into ten folds which became ten trials (ten trials for right and ten trials for left-hand imagination). Similarly, this process was applied to another input which is real input but, in this phase, the input was recorded for only ten seconds in order to keep it as a "real time analysis". Different paradigm was utilized in this phase where the imagination of right- and left-hand were arbitrarily displayed on the screen with similar period per trial.

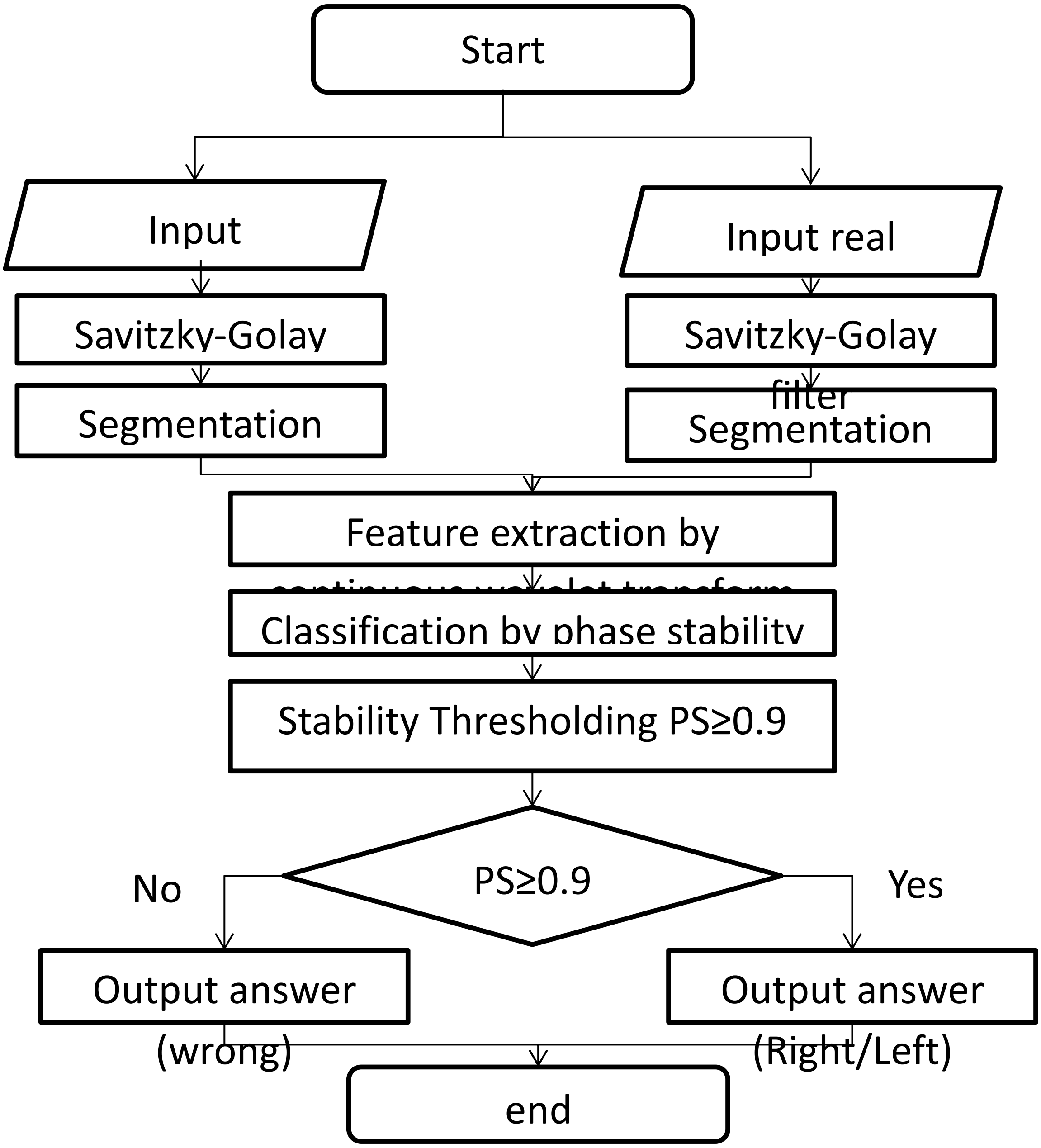


Figure 3 Flowchart of the methodology for algorithm.

Feature extraction and classification technique

Signals underwent the feature extraction process by continuous wavelet transform with complex Gaussian function of 4th order derivative (based on equation (4)) where both reference and real inputs were compared. The scale parameter was applied by the value of 110 and pseudo frequency was obtained by

$$f_a = Tf_\psi / a \tag{3}$$

where f_a is denoted as frequency at instantaneous scale, a is a scale, and Tf_ψ is a "pseudo" frequency at instantaneous scale.

As the phase stability analysis becomes the basis of signal processing used in our system, we considered the analysis of the synchronization stability, where the derived phase locking was adapted and implemented in the measured signals. Below is the mathematical expression for developing phase synchronization stability measurement.

In this study, 4th derivative was utilized as a complex Gaussian function as wavelet by following the notations in Strauss *et al.* (2006)

$$\psi_{a,b}(\cdot) = |a|^{-1/2}\psi((\cdot - b)/a)$$

where $\psi \in L^2(\mathbb{R})$ is the wavelet with $0 < \int_{\mathbb{R}} |\Psi(\omega)|^2 |\Psi(\omega)|^{-1} d\omega < \infty$ ($\Psi(\omega)$ is the Fourier transform of the wavelet), and $a, b \in \mathbb{R}, a \neq 0$). Thus, the wavelet transform is given as

$$\mathcal{W}_\psi : L^2(\mathbb{R}) \rightarrow L^2\left(\mathbb{R}^2, \frac{\mathrm{d}a\mathrm{d}b}{\mathrm{a}^2}\right) \tag{4}$$

By following the notation from Rosenblum *et al.* (2001), the synchronization stability is defined as

$$\Gamma_{a,b}(\mathcal{X}) := \frac{1}{M}\left|\sum_{m=1}^{M} e^{\imath \arg\left((\mathcal{W}_\psi \chi_m)(a,b)\right)}\right| \tag{5}$$

where $\Gamma_{a,b}$ of sequential $\mathcal{X} = \{\chi_m \in L^2(\mathbb{R}) : m = 1, \ldots, M\}$ of M sweeps. For the perfect neural synchronization, stability is indicated in a value of (0,1). Although perfect coherent phases can be obtained, the stability tends to decrease as a result of phase jittering. Then, as the phase difference is obtained by

$$e^{\imath\left(\arg\left((\mathcal{W}_{\psi}\chi_m)(a,b)\right)-\arg\left((\mathcal{W}_{\psi}\mathcal{Y})(a,b)\right)\right)} \tag{2}$$

where phase $\arg\left((\mathcal{W}_{\psi}\mathcal{Y})(a,b)\right)$ of a virtual reference signal $\mathcal{Y}$ in which m is constant in scale and time. For this calculation, the result of stability remains unchanged. Although this is discernible in mathematical sense, it shows the relation of stability criteria to phase locking measurement form two signals and oscillators.

Extracted signals were measured in a similar technique, phase synchronization stability analysis where both reference and real time signals by the application of phase locking value (PLV) that varies from 0 to 1. The higher the value indicated the better stability between two phases of input signals. Comparatively, this technique produces quite similar result as in the technique of wavelet-coherence and correlation coefficient. Nevertheless, it is observed that among these techniques, wavelet-phase stability is the most significant to be utilized in BCI system as it gives better significant differences between different classes of task.

In this process, the data was displayed in time-frequency representation and the level of stability was indicated by color-based image texture.

Thresholding the phase stability features

Thresholding is a method utilized in image processing to simplify the complexity of signal processing. Regardless, it also can be applied in this study as we used the time-frequency representation as the intensity-based segmentation. From the scale-time representation of classified signal, the selected data was summed from the value of averaged phase stability by the given condition

$$P_{n,m} = \begin{cases} 1 & p_{n,m} \geq T \\ 0 & p_{n,m} < T \end{cases} \tag{2}$$

where $P_{n,m}$ is the resulting pixel of phase stability at the (n, m) coordinate where n is the x-axis and m is the y-axis with the constant thresholding value, $T = 0.9$. Thus, level of intensity-based representation that were less than the thresholding value were ignored while the coordinates more than thresholding value were subsequently summed up which consist of C3, C4, and CZ from reference and real-time experiment. Afterwards, it went through the process of decision-making followed the condition below. If:

1. $P_{C3}(left) + P_{C4}(left) + P_{CZ}(left) > P_{C3}(right) + P_{C4}(right) + P_{CZ}(right)$; then "left" output will be displayed.

2. $P_{C3}(right) + P_{C4}(right) + P_{CZ}(right)P_{C3} > (left) + P_{C4}(left) + P_{CZ}(left)$; then "right" output will be displayed.

3. $P_{C3}(right) + P_{C4}(right) + P_{CZ}(right)P_{C3} = (left) + P_{C4}(left) + P_{CZ}(left)$; output will display "try again".

Evaluation and validation of performance

The evaluation of BCI system performance was constructed based on the method of confusion matrix [24]. This method is defined as performance accuracy of classification between two classes i.e. right-hand imagination and left-hand imagination. The advantage of this performance evaluation is the practice of examining large database can be easily observed to predict if the designed model is confusing the matrix, for instance, mislabeling as one another. Besides, it shows the percentages of correctly classified data over the total number of data inputs into the confusion matrix. Furthermore, the overall average accuracy would also be quantified.

The confusion matrix model was designed based on the total outcomes of the ten participants. The model constitutes for types of predictive variables which are true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Below are the descriptions for every term from the designed model:

1. True positives (TP): These are cases when we predicted 'yes' for they are able to produce correct outcomes (which in this experiment, right or left-hand imagination outcome).

2. True negatives (TN): We predicted "no", and they produce wrong outcomes.

3. False positives (FP): We predicted "yes", but they actually produce wrong outcomes.

4. False negatives (FN): We predicted "no", but they produce correct outcomes.

RESULTS AND DISCUSSION

Experimental results

In the present study, it was observed that the acquired EEG signals based on selected electrodes which are C3, C4, and CZ displayed non-error oscillations. The raw signals were then undergoing the segmentation process where the raw signals were cut into 10 trials and each trial contains 2560 samples. In Figure 4.4, it shows a plotted graph of amplitude against time in seconds for single trial. Each of the segmented signal was smoothed by using Savitzky-Golay filter. The filter was compared with another signal smoothing method namely moving-average (MA) filter in order to choose better implementing filter.

Signals comprise of both desirable and undesirable information that might contain a frequency or a range of frequencies. Moving average filter is a low-pass filter (LPF) which averaging all data points. MA filter is a type of filter that easy to understand, thus it is applied in most research. In the table, it shows the filtered signal by Savitzky-Golay filter, where the output is almost identical to the output signal by MA filter. However, it was clearly shown that there exist major differences of amplitude size between the signals.

Table 1 Comparison between original and filtered signals

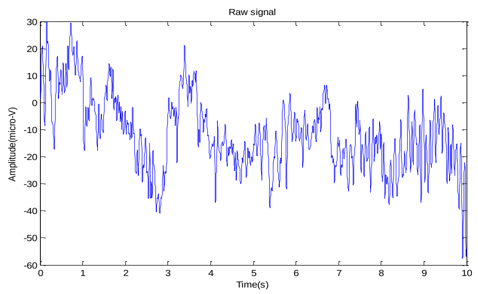
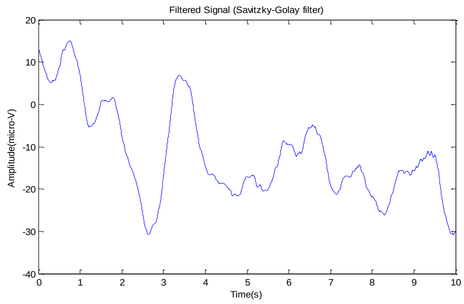
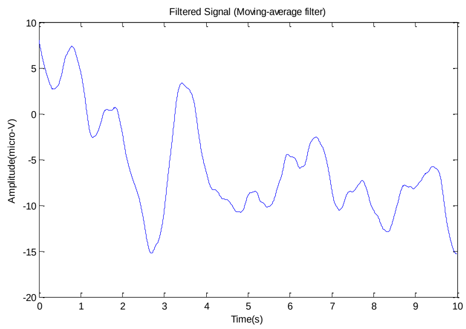
Original signal (noisy signal)	
Filtered signal by Savitzky-Golay filter	
Filtered signal by moving average filter	

Table 2 Comparison between original and filtered signals.

Frame/window length	S-G filter (SNR)	M-A filter (SNR)
255	6.2914	2.0049
127	8.3706	3.6403
63	9.5778	5.3146

From Table 2, it shows the comparison between two filters that had been discussed. The value of window and frame length are varied and a large gap of SNR values can be observed between both filters. This shows that the implementation of Savitzky-Golay filter outperforms the MA method. Similar previous research on EEG experiment also implemented these techniques. The results reaffirm that Savitzky-Golay method produces better SNR than MA filter.

Analysis of decision outcomes

Analyses conducted were focusing on two outcomes which are right-hand decision and left-hand decision. Table 3 shows the comparison for left and right imagination tasks in the form of scale against time representation of wavelet-phase stability analysis. The analysis of stability was measured between two inputs signal which are reference signal and real-time signal. The stability between these two signals were assessed by indicating a range of phase stability from 0 which is unstable to 1 which is the highest stability in this evaluation. High intensity of stability values was dominated on the first second until the third second for both right and left imagination. It was observed that the right imagination (targeted output) produced higher intensity for every channel which are C3, C4, and CZ than left imagination (non-targeted output). It implies that the subject was able to trigger right-hand output when the online motor imagery task was in progress while rejected the left imagination analysis as it produced lower intensity.

Table 3 Right-hand decision outcome.

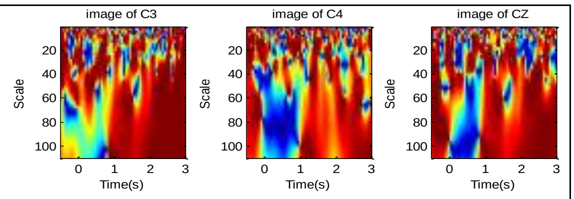
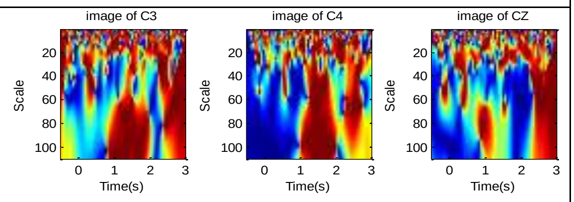
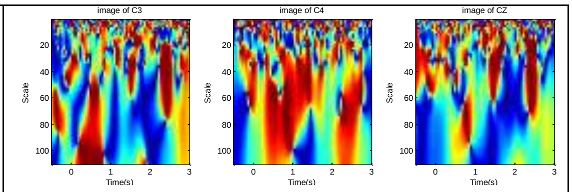
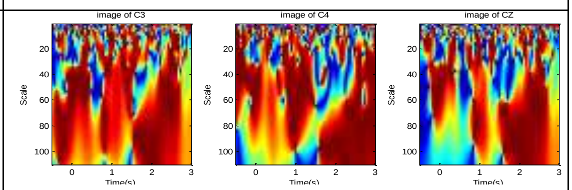
Right (Target output)	
Non-target output	

Table 3.1 The general calculation of confusion matrices. This technique is widely used in evaluating the performance of classification model.

		Actual		
		Target	Non-target	**Total**
Predicted	Target	TP	FP	TP+FP
	Non-target	FN	TN	FN+TN
Total		TP+FN	FP+TN	TP+FP+FN+TN

In contrast, motor imagery experiment was also conducted to observe the left motor output. But it can be seen that the domination of high intensity was produced throughout the time for both right and left imagination on all channels. However, it shows that intensity was produced higher on the left imagination (targeted output) than the right imagination (non-targeted output) of reference and real time signals measurement. Thus, results on Table 4 shows the subject for this task was successfully performs left-hand imagination of decision output.

Table 4 Left-hand decision outcome.

Non-target output	
Left (Target output)	

Next, Figure 4 shows the bar graph of total presence of true imaginary for right-hand imagination and left-hand imagination which are indicated in blue and orange bars, respectively. On the y-axis, the total of present imagination refers to a situation where subjects were able to produce correct decision outcomes based on the tasks given. From the graph, it can be seen that the highest number of total right imaginary outcome is on subject 2 with a score 10 out of 10 while the total number of lowest was on subject 9 with 6 scores. On the other hand, for the left-hand imaginary, subject 2 was able to produce 8 true outcomes while the lowest hit on subject 5 with 6 scores. Overall, the total imaginary of right decision outcomes were higher than the left outcomes. We can conclude that most of the participants tend to perform better on right-hand imaginary than the other side. However, this result could still be improved and balanced as to produce a firm and robust BCI signal processing technique.

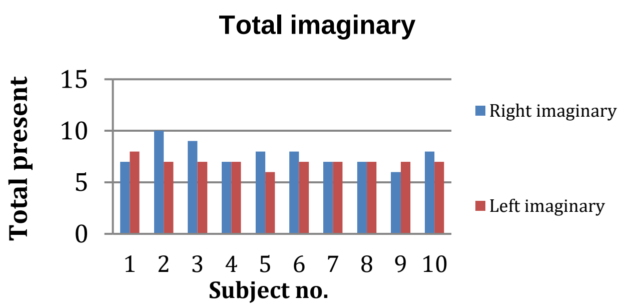


Figure 4 Flowchart of the methodology for algorithm.

Performance evaluation

The evaluation of the implemented BCI processing was observed by using the technique of confusion matrices. Two types of measurement that had been utilized in this method are the calculation of confusion matrix by right imagination as the output decision (see Table 4.5) and left imagination as the output decision (see Table 4.6). Finally, the confusion matrices were constructed with the determination of false positives, false negatives, true positives, and true negatives based on all participants results.

There were 200 numbers of outcomes evaluated on confusion matrices technique where 100 for left decision outcomes and another 100 from right decision outcomes. From Table 5, it shows that all participants produced 107 of total predicted outcomes and 93 outcomes for non-target outcomes. As the validation of performance, it shows the model was successful in attaining 72% of overall operation of the system which is considered as a good performance. Besides, based on the classification algorithm, this model was able to classify 75% precision of overall proportion in producing targeted outputs which correspond with the actual output decisions. Furthermore, this model also produced 77% sensitivity that tells us the proportion of actual target outcome, which in this case is right outcomes was predicted by algorithm as producing targeted outcomes. Next, for the specificity, 70% of the proportion of participants did not produce non-targeted outcomes and were predicted by the model as non-targeted (which is in this case is left outcomes).

Table 5 Confusion matrix for right-hand decision as a target output.

		Actual		
		Right	Non-right	Total
Predicted	Right	77	30	107
	Non-right	23	70	93
Total		100	100	200

From Table 6, it shows that all participants produced 93 of total predicted outcomes which is left-hand and 107 outcomes for non-target outcomes which is right hand. As the validation of performance, it shows the model achieved 74% of overall operation of the system which is considered as good performance as similar as the preceded confusion matrices. Furthermore, from the classification algorithm, this model was able to classify 75% precision of overall proportion in producing targeted outputs correspond with the actual output decisions. On the other hand, this model produced 70% sensitivity that tells us the proportion of actual target outcome, which in this case is left outcomes was predicted by algorithm as producing targeted outcomes. Next, 77% specificity was reported where 77% of the participants did not produce non-targeted outcomes and were predicted by the model as non-targeted (which is in this case is right outcomes).

Table 6 Confusion matrix for left-hand decision as a target output.

		Actual		
		Left	Non-left	Total
Predicted	Left	70	23	93
	Non-left	30	77	107
Total		100	100	200

From the evaluation of the performance, it shows that the implemented classification algorithm was able to attain high accuracy of more than 70% which is the benchmark of good performance. From both calculation of confusion matrices tables, it shows a balanced trade off of the result thereby affirmed the model as considerable and significant.

The results were compared with the previous studies to obtain the benchmarks for the classification accuracy. Previously, a research was conducted on implementing the support vector machine (SVM) as a classification of features and result produced below 70% of classification accuracy [13]. Although SVM is one of the most common methods used to isolate different classes of feature, it is unable to classify every single feature which might lead to the loss of important information in particular features. Apart from that, in [25], BCI experiment was conducted by using K-Nearest Neighbor approach as a classification of feature. With the average accuracy of 53%, this shows that K-Nearest Neighbor approach has low reliability in solving multiclass problems. These imply that our proposed technique produced better results and can be utilized in classifying multiclass problems.

Nevertheless, there are other methods that are far superior than the proposed technique in solving problems of other related disciplines. For instance, a technique utilized by [26] produced 81% of accuracy using Linear Discriminant Analysis (LDA). The advantage of utilizing that technique is that LDA is mathematically simple and computationally efficient but additional feedback delay may occur during computational process. For our technique, it is feasible to measure large neural correlates. Thus, it produces more meaningful data while acquiring the broad-band signal phase.

CONCLUSION

In this paper, we proposed the algorithm based on phase stability analysis for feature classification of two-class motor imagery-based brain-computer interface. The new method was incorporated with continuous wavelet transform as a feature extraction. Prior to that, a signal smoothing technique was implemented which is Savitzky-Golay filter to optimize the signal-to-noise ratio (SNR). Experimental results have shown that with overall classification accuracy over 70%, it can be concluded that the proposed technique is considerably good and reliably utilized. Future works may involve other types of BCI experiment such as P300 event-related potential and steady-state visual evoke potential for further application of phase stability analysis.

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