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OPTIMIZATION OF LEAST SQUARES SUPPORT VECTOR MACHINE TECHNIQUE USING GENETIC ALGORITHM FOR ELECTROENCEPHALOGRAM MULTI-DIMENSIONAL SIGNALS

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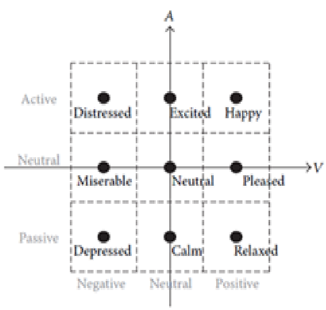
Graphical abstract



Abstract

Human-computer intelligent interaction (HCII) is a rising field of science that aims to refine and enhance the interaction between computer and human. Since emotion plays a vital role in human daily life, the ability of computer to interpret and response to human emotion is a crucial element for future intelligent system. Accordingly, several studies have been conducted to recognise human emotion using different technique such as facial expression, speech, galvanic skin response (GSR), or heart rate (HR). However, such techniques have problems mainly in terms of credibility and reliability as people can fake their feeling and response. Electroencephalogram (EEG) on the other has shown to be a very effective way in recognising human emotion as this technique records the brain activity of human and they can hardly be deceived by voluntary control. Regardless the popularity of EEG in recognizing human emotion, this study field is relatively challenging as EEG signal is nonlinear, involves myriad factors and chaotic in nature. These issues have led to high dimensional problem and poor classification results. To address such problems, this study has proposed a novel computational model, which consist of three main stages, namely a) feature extraction; b) feature selection and c) classifier. Discrete wavelet packet transform (DWPT) has been used to extract EEG signals feature and ultimately 204,800 features from 32 subject-independent have been obtained. Meanwhile, Genetic Algorithm (GA) and Least squares support vector machine (LS-SVM) have been used as a feature selection technique and classifier respectively. This computational model is tested on the common DEAP pre-processed EEG dataset in order to classify three levels of valence and arousal. The empirical results have shown that the proposed GA-LSSVM, has improved the classification results to 49.22% and 54.83% for valence and arousal respectively, whereas is it observed that 46.33% of valence and 48.30% of arousal classification were achieved when no feature selection technique is applied on the identical classifier.

Keywords: EEG signal, human emotion recognition, feature selection, LS-SVM

Abstrak

Interaksi manusia-komputer pintar (HCII) merupakan satu kemajuan dalam bidang sains yang bertujuan untuk memperbaiki dan meningkatkan interaksi antara komputer dan manusia. Oleh kerana emosi memainkan peranan yang penting dalam kehidupan seharian manusia, keupayaan komputer untuk mentafsir dan tindak balas terhadap emosi manusia adalah elemen yang penting untuk sistem pintar pada masa hadapan. Sehubungan dengan itu, beberapa kajian telah dijalankan untuk mengenalpasti emosi manusia dengan menggunakan pelbagai teknik seperti ekspresi muka, ucapan,tindak balas kulit galvanic (GSR), atau kadar denyutan jantung. Walau bagaimanapun, teknik-teknik tersebut mengalami masalah terutamanya dari segi kredibiliti dan kebolehpercayaan seperti yang seseorang boleh memalsukan perasaan dan tindak balas mereka. Electroencephalogram (EEG) adalah satu teknik lain yang telah terbukti sebagai satu cara yang sangat berkesan dalam mengenalpasti emosi manusia kerana teknik ini merekod aktiviti otak manusia dan hampir tidak boleh ditipu oleh kawalan secara sukarela. Walaupun teknik EEG popular dalam mengenalipasti emosi manusia, bidang penyelidikan ini agak mencabar kerana isyarat EEG tak linear, melibatkan faktor-faktor yang pelbagai dan tidak berstuktur secara semulajadi. Isu-isu ini telah membawa kepada keputusan pengkelasan miskin dan masalah dimensi yang tinggi. Untuk menangani masalah-masalah tersebut, kajian ini telah mencadangkan satu model pengiraan novel, yang terdiri daripada tiga fasa utama iaitu a) ekstrak ciri ; b) pilihan ciri dan c) pengelas. *Discrete wavelet packet transform* (DWPT) telah digunakan untuk mengekstrakan ciri-ciri isyarat EEG dan akhirnya 204,800 ciri dari 32 subjek terasing telah diperolehi. Sementara itu, algoritma genetik (GA) dan *Least squares support vector machine* (LS-SVM) telah digunakan sebagai teknik pemilihan ciri dan pengelas. Model pengiraan ini diuji pada pangkalan data EEG umum, DEAP yang terlebih dahulu telah diproses bagi mengklasifikasikan tiga tahap *valence* dan *arousal*. Keputusan empirikal telah menunjukkan bahawasanya cadangan DWPT-GA-LSSVM, telah mempertingkatkan hasil klasifikasi *valence* dan arousal kepada 49.22% dan 54.83% masing-masing, sedangkan hasil penyelidikan telah menunjukkan bahawa 46.33% daripada valence dan 48.30% klasifikasi arousal dicapai apabila tiada teknik ciri pemilihan digunakan pada pengelas yang serupa.

Kata kunci: Isyarat EEG, kenalpasti emosi manusia, ciri pemilihan, algoritma genetik, LS-SVM

1.0 INTRODUCTION

Emotion is vital for humans, it is not only giving a share in communication between people, but in addition presents an important role with logical and intelligent behaviour and its features can be viewed in several areas of our life [1, 2]. Therefore, HCII is a rising field of science that aims to refine and enhance the interaction between computer and human. Since emotion plays a vital role in human daily life, the ability of computer to interpret and response to human emotion is a crucial element for future intelligent system. Hence, emotion recognition study is indispensable [1, 2]. Assessing human emotion can carries out by analyzing either physiological signals or psychological signals. In physiological aspect, human emotion could be recognised based on facial expression and prosody recognition. Meanwhile, in psychological aspect, the physiological signals could be dividing to the couple of categories, which are the peripheral nervous system such as Galvanic Skin Response (GSR), Electromyography (EMG), and Heart Rate (HR), and the others are provided from the central nervous system which called neurophysiologic signals such as Electroencephalogram (EEG) [3, 4].

Accordingly, several studies have been conducted to recognise human emotion using different technique such as facial expression, speech, GSR, or HR. However, such techniques have problems mainly in terms of credibility and reliability as people can fake their feeling and response [1]. EEG on the other hand has shown to be a very effective and reliable technique in recognising human emotion as this technique records the brain activity of human and they can hardly be deceived by voluntary control, Recently, this technique attracts the attention of many studies, and numerous models have been conducted based on this technique [1, 4, 5, and 6]. Regardless the popularity of EEG in recognizing human emotion, this study field is relatively challenging as EEG signal is nonlinear, involves myriad factors and chaotic in nature. These issues have led to high dimensional problem and poor classification results [4, 6, 7, 8, and 9]. To overcome such problems this study has proposed a novel computational model, which consist of three main stages include features extraction stage, feature selection stage, and classification stage. In this study, this new computational model is tested on the common DEAP pre-processed EEG dataset in order to classify three levels of valence and arousal.

2.0 LITERATURE REVIEW

As human emotion is very important, a high number of studies attempt to recognise human emotion. Several techniques could be used in recognising human emotions based on physical signals such as facial expression, prosody, HR, GSR, and EMG. Other techniques based on psychological signals such as EEG have also being used. Recently, EEG-based human emotion recognition technique has shown to be very effective and reliable technique in recognising human emotion, beside the less resolution which is hold. Hence, this technique attracts the attention of many researchers, and numerous models have been conducted based on this technique. Most of researchers depend on the general EEG-based emotion recognition approach which is consist of three phases include pre-processing, features extraction, and classification phases. However, practically feature extraction and classification methods are the most important methods which must be chosen carefully. Hence, several methods could be suggested to be used within several studies. Additionally, some studies used a primary EEG datasets and others use secondary EEG datasets which are available over internet such as DEAP dataset. Therefore, feature extraction methods categorised under mainly three domains include (1) Time domain, (2) Frequency domain, and (3) Time-Frequency domain. Several methods have been suggested to use under the first two categories such as Event Related Potentials (ERP), Statistics of Signal, Hjorth Features, Fractal Dimension, and Higher Order Crossings (HOC) as time domain methods, and Band Power and Higher Order Spectra (HOS) as frequency domain methods. However, due to the several limitations of the frequency domain and time domain analysis, numerous time-frequency algorithms have been previously proposed in previous studies such as Hilbert-Huang Spectrum (HHS), short-time fourier transform (STFT), and Wavelet Transform (WT) [10, 11].

Horlings et al. [12] have used frequency-domain based features where cross correlation power with alpha power was extracted, while Anh et al. [13] used time-domain based features where fractal dimension was extracted, and both of these studies have used SVM as a classifier. However, the classification accuracy obtained is 71.0% for valence and 81.0% for arousal states from the first one, and 70.5% from the latter. Moreover, Khalili and Moradi [14] have used FFT as a feature extraction method and K-Nearest Neighbors (KNN) as a classifier in order to classify multi-class of human emotions, the accuracy result obtained is 40.0% and 51.0 for valence and arousal states respectively. Additionally, Petrantonakis and Hadjileontiadis [15] and Wang et al. [16] studies, both of them employed a model for recognising multiclass emotions based on EEG and used they have been used SVM as a classifier, however, the first one used HOC and the latter used FFT as a feature extraction methods, whatever, the classification accuracy obtained is 83.33% and 61.5 respectively. Bajaj and Pachori [17] have suggested to use time-frequency based feature extraction method using multiwavelet decomposition where entropy value was calculated for each sub-signal and used as an input into multiclass least square support vector machine (MC-LS-SVM) classifier in order to classify four emotions include happy, neutral, sadness, and fear, and The accuracy results obtained is 80.83%. However, in another study of Bajaj and Pachori [18], they tried to classify same emotions, whereby they proposed to use combination of different feature extraction method based on time-frequency and time domain where they used multiwavelet decomposition and the mean and standard deviation for sub signals was calculated and used as an input features into MC-LS-SVM classifier, and the classification accuracy obtained is 91.04%. Liu et al. [19] have proposed Imbalanced Quasiconformal Kernel-Support Vector Machine (IQK-SVM) as a classifier, and they used frequency-domain feature extraction method involve on spectra power of different frequency bands as an input features into the classifier, in order to classify two arousal and valence classes, where the classification accuracy obtained is 83.71%. In another hand, selecting the appropriate classifier can extremely affect the classification performance, for example, in the studies of Khalili and Moradi [14] and Wang et al. [16], both of them used FFT as feature extraction method, but they used different classifier to classify multiclass of human emotions, whereby the first one used SVM classifier and the classification accuracy obtained is 66.5%, and the latter used KNN classifier and the classification accuracy obtained is 40.0% and 51.0% for valence and arousal states respectively.

Therefore, although there are many effective classifiers, and many effective methods for feature extractions methods which are extract features from EEG signals, high number of features could cause myriad feature space dimensionality that is come from the number of electrodes used and/or number of trails and/or number of frequency bands considered and/or number of subjects. For instance, based on 32 electrodes x 40 trails x 5 bands x 32 subjects, 204800 number of feature are obtained which could cause the curse dimensionality problem, which in turn leads to negatively affect on the classification accuracy. Hence, several studies tried to decrease the number of features by decrease number of electrodes such as or by decrease the number of features itself by performed feature selection in order to select subset of features. For example, Ansari et al. [20] have filter selection using synchronization likelihood method in order to select the most related hjorth parameters features correlated with 3 classes, which then classified using Linear Discriminant Analysis (LDA) classifier, and the classification results obtained was 51.7%. meanwhile, Chanel et al. [21] in another study have proposed filter features selection based on fast correlation-based feature (FCBF) selection and it was applied on the high number of features extracted, whereby 9 bands form 4-20Hz have been extracted from each subject, and the y obtained accuracy results at 76.0% using LDA classifier for three classes. However, several studies such the studies of Åberg and Wessberg [22] and Saeys et al. [23] claimed that the wrapper selection technique is superior the filter selection technique. Unlike filter technique, in wrapper technique the selection is evaluated simultaneously with the classifier and usually heuristic algorithms is used for this purposes such as genetic algorithm (GA). For example, Hosseini et al. [24] have performed feature selection based on GA and SVM classifier, and they got an improved classification accuracy result in 82.4%. In another hand, Li and Lu

[25] tried to classify two classes of emotion include happy and sad, and they have performed wrapper feature selection based on common spatial pattern (CSP) algorithm and SVM and they got a better result where the classification accuracy was 93.5%. This paper proposed to use wrapper feature selection based on GA and LS-SVM classifier for selecting from time-frequency domain features. Data acquisitions and the methodology used in this study are explained further in this paper.

3.0 METHODOLOGY

This section presents the model that is used in recognising human emotions as illustrated in Figure 1. In this paper, mainly two tests were implemented, one without feature selection and the other one with feature selection in order to see the impact of feature selection and compare the results. This study proposed to use the pre-processed EEG dataset from DEAP database. In addition, this study only used the data recorded from the brain (EEG signals). The methods used in this study are described in next subsections.

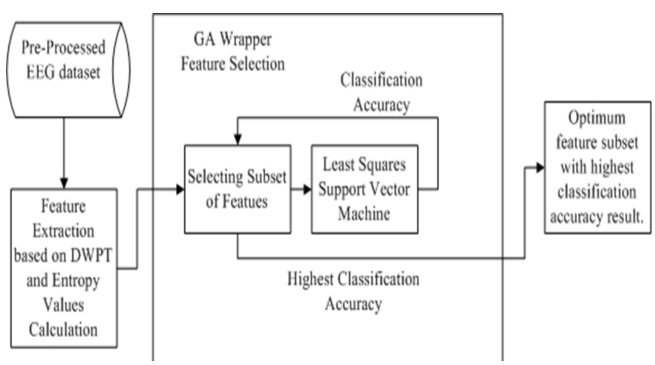


Figure 1 The proposed EEG emotion recognition model

3.1 EEG Database

This study has tested the proposed model on the DEAP database. This database contains information on valence, arousal, and dominance. Generally there is two types of datasets, one is original dataset, and the other one is a pre-processed dataset (more information about DEAP database can be found in [26]. 32 subjects have participated for the DEAP database collection. In this experiment, subjects' emotion is induced by using visual-audio stimuli, which is one minute music video, where 40 music videos are used. Moreover, 32 EEG channels based on Biosemi ActiveTwo device [27[were used for data recording, where the sampling rate is 512 Hz. The Manikins' self-assessment was made for the 32 subjects, whereby, all recorded data are labelled with the corresponding arousal, valence, dominance, and like/dislike values ranging from 1 to 9. However, according to Russell [28], the valence and arousal dimensions are sufficient enough for determining an emotion. Therefore, although the DEAP dataset provides four emotion state including low arousal/low valence (LALV), high arousal/low valence (HALV), low arousal/high valence (LAHV), and high arousal/high valence (HAHV), in this paper and similar work of Jirayucharoensak et al. [6], this emotion has been mapped from 1–9 scale into 3 levels for each valence and arousal. The valence scale from 1 to 3 is mapped to "negative", scale 4 to 6 is mapped to "neutral," and scale 7 to 9 is mapped to "positive," respectively. Meanwhile, the arousal scale 1 to 3 is mapped to "passive", scale 4 to 6 is mapped to "neutral", and scale 7 to 9 is mapped to "active" respectively. Hence, based on the brand-new scale mapping, 9 emotion classification states are obtained include distressed, miserable, depressed, excited, neutral, calm, happy, pleased, and relax as shown in Figure 2.

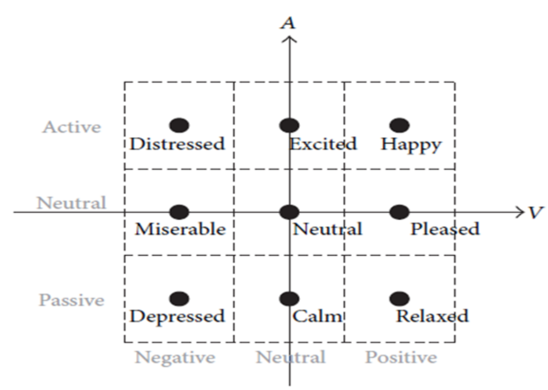


Figure 2 Pre-defined DEAP emotion states [6]

Moreover, in order to decrease the probability of any significant information lost, this study suggest to use the EEG signals that are obtained from all 32 brain electrodes offered in the DEAP dataset which includes Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4, and O2. The signals from different electrodes are preserved as it's interrelated and play an important role in inducing human emotion states.

3.2 Subjects

Commonly human recognition model can be divided into two categories, (1) subject-dependent model, and (2) subject-independent model. However, subject-independent model is more challenging than the subject-dependent model due to intersubjects variability [29]. As a result, this study has proposed to use subject independent model, in which this study attempt to address problems associated with intersubjects problem, and it may open a new possibility to compare with other studies that has used same data.

3.3 Pre-processing Phase

EEG signals are generally recorded through various positions on the top of the head/ scalp. These signals are usually contaminated with artifacts and noises such as electro-oculogram (EOG) signals, electrocardiography (ECG) signals, and due to power line such as 50Hz power line noise, etc. These artifacts must be removed in order to get better quality and valuable of EEG data signals [30, 31]. However, this study proposed to use the pre-processed EEG datasets (DEAP) which is already pre-processed by Koelstra et al. [26]. Several modifications have been performed on the EEG signals for instance: At first, the sample rate of the data has reduced from 512Hz to 128Hz. Secondly, the artifcats of eye movements have removed from the EEG signals by using a technique that discussed in their study [26, 32]. Thirdly, the EEG signals have filtered with a band pass filter in the range between 4Hz and 45. Finally, the EEG data has divided into several segments, whereby each segment includes 60 second samples with elimination of the first 3 seconds. Hence, the pre-processing phase will not be performed in the context of this study.

3.4 Feature Extraction Phase

EEG signals are nonstationary in nature. Discrete wavelet transform (DWT) is a feature extraction method under time-frequency domain and it is shown to be more suitable for such signals, whereby the nonstationary signals seems to have different frequencies at different times. Hence, DWT is the appropriate method in decomposing EEG signals into different frequency bands which are hold information in time and also in frequency domain [33, 34]. Therefore, DWPT is implemented for efficient and virtuous frequency band localization. Additionally, unlike normal WT, the DWPT decomposes high and also low frequency component of signals into any required decomposition level, as Figure 3 illustrates five levels DWPT decomposition. In this study, DWPT is applied on the EEG signals in order to obtain five frequency band called theta, alpha, beta1, beta2, and gamma. Later, the entropy value for each element is calculated through DWPT decomposition.
The DWPT algorithm was developed and implemented under Matlab software environment, where the proposed frequency bands were extracted and the entropy features for each band is calculated. In the development of DWPT algorithm, this study have used the Matlab function “wpdec” for signals decomposing and the Matlab function “wpcoef” for coefficient calculation. Then in other hand, the matlab function “wentropy” is set for computing the entropy values in order to get entropy features of the signals. The EEG signals were decomposed based on the Daubechies 4 discrete wavelet (db4). This is due the fact that the wavelet db4 was shown best in representing five level decomposition of the EEG signals as illustrated in Figure 3 [34]. This algorithm is performed for all 32 subjects and the obtained features are used as input into the classifier, where finally, 204800 numbers of extracted features space for all subjects are obtained.

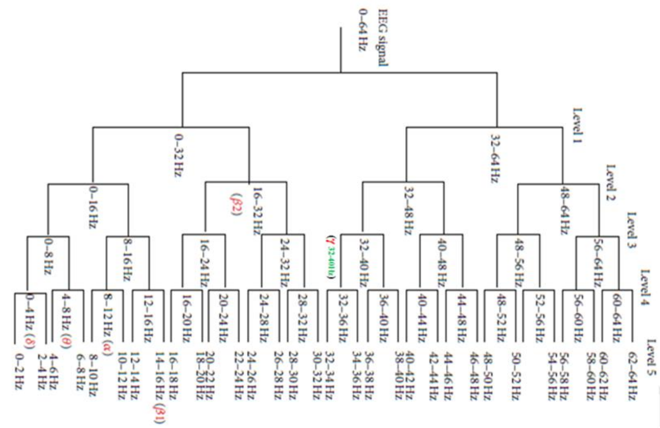


Figure 3 Five levels decomposition EEG signals based on DWPT [34]

3.5 Feature Selection Phase

To address the high dimensionality feature space problem, this study has proposed a feature selection phase, in which the subset of relevant features is selected to increase the classification accuracy. Thus, genetic algorithm along with LS-SVM classifier is proposed in this study. GA is the algorithm that is suitable for multi-dimensional problem and unlike the gradient search methods, GA avoid the local optima problem. Additionally, GA algorithm has exhaustive and high search space exploration ability. This algorithm is based on the mechanism of natural evolutionary criteria which is designs to mimic the biological practice in order to optimise complicated cost function. The optimization is simply obtains by means of enabling a population made up of a lot of individuals to advance underneath specific and certain rules to suggest that maximizes the actual fitness [7, 8, 35]. In this study, GA is implemented under Matlab software environment. The wrapper selection based on GA and LS-SVM classifier code is constructed. The individuals of the population were set as binary strings 1 and 0 which indicates the consideration of selected feature, whether the feature included and not included respectively. Meanwhile the fitness function is set as the classification accuracy. Table 1 illustrates the options parameters setup for GA algorithm in this study.

Table 1 Options parameters setup for GA

No.	Parameters	Description
1	Individuals	Bit string (0,1)
2	Fitness value	Classification accuracy
3	population size	20
4	Crossover pint	2-point
5	Scale	0.8
6	mutation rate	0.2

3.6 Classification Phase

In the classification phase, the effectiveness of a subset of features is evaluated by using LS-SVM. The LS- SVM has been proposed by Suykens and Vandewalle [36]. LS-SVM has showed to take less computational effort compared with origin SVM's. The LS-SVM is actually the simplified version of SVM. In another hand, the LS-SVM classifier is a supervised learning system which is based on statistical learning theory.

The entropy features which are calculated based on the DWPT feature extraction method and were taken as an input of LS-SVM classifier. In addition, this study used to classify more than two classes. This multiclass problem can be solved by considered the training data $\{x_i, y_i^k\}_{i=1,\ k=1}^{i=P,\ k=m}$, where x_i is the training input pairs, and y_i^k is the k^{th} output for pattern i, p, and m denote the number of training input pairs and also the number of hyperplenes, respectively [17, 18]. For more details about the multiclass LS-SVM analysis, please refer to [17, 18, and 36]. There are also several kernel functions include RBF, linear kernel, and quadratic kernel that have been widely used by many studies. In this study, the RBF kernel function is typically chosen. The formulation of the RBF kernel for MC-LS-SVM is $K(x, x_i) = exp\left\{\frac{-\|x-x_i\|_2^2}{\sigma_k^2}\right\} = e^{-\frac{|x-x_i|^2}{2\sigma_k^2}}$, where the width of RBF kernel is controlled by the σ_k^2 parameter [17, 18]. Furthermore, the LS-SVM and kernel parameters is automatically tuned using grid search method.

3.7 Evaluation Phase

The following sub-sections detailed out the evaluation metric for this proposed method.

3.7.1 Cross-Validation (CV)

Cross-validation is a method for evaluating and comparing learning algorithms. CV is divide data into two parts, one for training and the other one for evaluation. The k-fold cross validation is the basic form CV. This study implemented 10-fold cross validation which divide the data into ten equal segment, and each segment is evaluated one with other remain segments [37]. Moreover, true positive points (TP), true negative points (TN), false positive points (FP), and false negative points (FN) are also calculated in this study.

3.7.2 Classification Accuracy

In this study, the classification accuracy is calculated for each individual in GA as a fitness value for each. The classification accuracy can be calculated by divides the number of correct decisions on the total number of cases, as in the following equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \qquad (1)$$

where TP and TN are the true positive and negative points respectively, and FP and FN are the false positive and negatives points respectively [38].

4.0 EXPERIMENTAL RESULTS

In our experiments, the capability of our proposed computational model was evaluated by mainly two experiments which include (1) computational model without feature selection and the other one (2) the computational model that is integrated with feature selection algorithm. In the first test, the EEG features from each 32 channels are extracted and the entropy values for these features are calculated. Approximately, 204800 numbers of features is obtained from this process. These features are used as an input into LS-SVM classifier for classification and evaluation processes. This process was employed one for valence and arousal classes separately. In the classification process, the EEG data features has 100 times randomly divided by 70% for training data and 30% for test data using "crossvalind" function. The classification process is repeated in a closed loop of 100 iterations, in which it aims to detect the highest accuracy result. The training data are then trained by 10-fold cross-validation and the trained model later is tested with the testing data. Ultimately the matrix with predicted output of the test data is obtained.

In another hand, in the second experiment test, this study tried to enhance and improve the efficiency of the model by integrated it with the GA in which the features are selected prior classification process. The GA options were first setup, with the population size set to 20, 2-point crossover probability at scale 0.8, and mutation rate at 0.2, where both of them are applied uniformly and the individuals of the population were binary strings. This new model is employed on valence classes and arousal classes separately. The comparison of accuracy between the two tests experiments in term of valence and arousal for 32 subject-independent are illustrated in Figure.4.

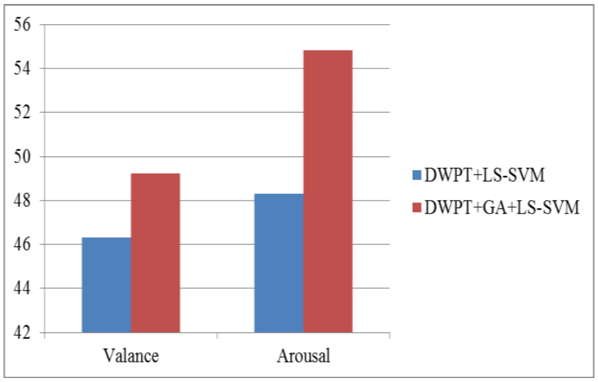


Figure 4 DWPT-LS-SVM versus DWPT-GA-LS-SVM accuracy of valence and arousal

5.0 DISCUSSION

The main purposes of this study are to explore the impact of the feature selection process and how the proposed model addressed high-dimensionality features. Additionally, this study aims to proof that the feature selection possibly can increases classification accuracy of EEG-based emotion recognition, and its ability in dealing with the intersubjects problem. In this study, four tests have been implemented which are listed in the following Table 2.

Table 2 Four different tests implemented in this study

Test No.	Number Of Classes/ Emotional Dimension	Model Used	Accuracy
1	3/Valence	DWPT-LS-SVM	46.33%
2	3/Arousal	DWPT-LS-SVM	48.30%
3	3/Valence	DWPT-GA-LS-SVM	49.22%
4	3/Arousal	DWPT-GA-LS-SVM	54.83%

Tests 1 and 2 have been implemented to classify three levels of valence and arousal respectively using DWPT-LS-SVM model. Meanwhile the test 3 and 4 have been implemented to classify three levels of valence and arousal respectively using the new model proposed (DWPT-GA-LS-SVM) where GA algorithm is integrated as a features selection phase. In the first two tests, this study observed that when the data is divided by 70% and 30% for training and testing respectively using fold crossvalind, the accuracy obtained is different and fluctuated. This is main due to the classifier parameters tuning for multiclass using grid search algorithm, and in return it has an effect on the accuracy of the classifier. Hence, in order to sure that the highest accuracy within particular test is obtained, repeating the classification process several times is important. The classification accuracy is coded inside close loop holds in one hundred iterations and the highest accuracy among them is considered. On another hand, in the latter two tests (test 3 and 4), the feature selection is considered as a solution for high dimensionality of feature space and intersubjects problems. Hence, by using the GA algorithm, the optimal subsets of features among 2000 generated subsets (20 individuals×100 generations) for each of both valence and arousal could be found, whereby the classification accuracy reaches at 49.22% and 54.83% respectively. Figure 5 below illustrated the results of GA feature selection implementation where Image A and Image B are the results for valence and arousal respectively, and the fitness function is classification accuracy.

Within the two images the two axes depict the highest fitness values (highest accuracy) among individuals against generation number. As observed, the fitness value represented as a negative value, because the GA algorithm is designed for minimization problem, hence, this study manipulated the representing of the accuracy value to be negative for optimisation purposes. Within the optimisation process of the valence classification, the fitness value is rapidly increased from the first to the second generation, which is approximately -44.0 and - 46.7 respectively. However, it is dramatically decreased directly in the third generation to be approximately -44.7. In another hand, within the optimisation process of the arousal classification, the fitness value is slightly increased from the first generation to second generation, which is approximately -52.0 and -52.5 respectively. However, it is back again to -52.0 directly in the third generation. Moreover, the fitness value is shown to be in fluctuation between the generation number 20 and 28 of the valence classification, and it is almost same state for arousal classification. Additionally, in Image A, although the fitness values over the generation numbers from 10 to 50 are wobbling, but the disparity over generations seems to be stable, and it is also clearer in Image B, where the inequality between the fitness values over generation seems to be more stable. However, one reason behind this, which is the inter-subjects problem and myriad number of features are there. However, the accuracy could be improved.

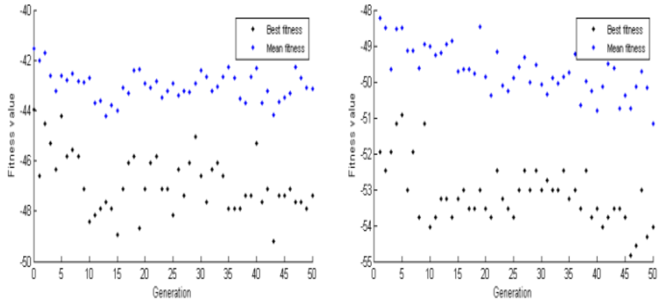


Image A: valance classification. Image B: arousal classification.

Figure 5 The fitness values of the best individual in each generation of GA

Lastly, the new model proposed has ability to deal with the high number of features and the intersubjects problem. The accuracy of valence and arousal classification could be improved from 46.33% to become 49.22% for valence and from 48.30% to become 54.83% for arousal. Therefore, similar to this study, a model has been proposed to deal with such problem and very significant results have been shown. Jirayucharoensak et al. [6] proposed a model for EEG emotion recognition and they applied it on the DEAP data to classy three levels of valence and arousal. They utilised deep learning network (DLN) classifier and used with the principal component analysis (PCA) and covariate shift adaptation (CSA) algorithms, they implement it with a stacked auto encoder (SAE) based on hierarchical feature learning approach. The classification accuracy obtained from applying this model was 55.07% and 52.56% for valence and arousal respectively, and they claimed that their algorithm (DLN) is superior existing algorithms. Table 3 shows summary of average accuracy results.

Table 3 Summary of average accuracy results

Model	Valence	Arousal
DWPT-GA-LS-SVM	48.30%	54.83%
DWPT-LS-SVM	46.33%	49.22%
PSD+DLN(PCA+CSA)	55.07%	52.56%
PSD+DLN	49.52%	46.03%

Indeed, the new model proposed in this study has shown better emotion recognition performance than most of existing model, and superior existing models in arousal classification. Moreover, using DWPT with LS-SVM classifier shown significant results, and they are a real promising algorithms in the field of affecting computing.

6.0 CONCLUSION

This study has proposed two computational models; (1) first model consist of DWPT algorithm for feature extraction and LS-SVM as classifier, while (2) second model the other one is new model where this study improved it by integrating genetic algorithm for feature selection with existing DWPT algorithm and LS-SVM as feature extraction technique and classifier respectively. These two models are implemented to recognise three levels of valence and arousal states, with four tests are performed separately. The classification accuracy of the new model (DWPT-GA-LS-SVM) is 49.22% for valence states and 54.83% for arousal states. Meanwhile, the classification accuracy for the other model (DWPT-LS-SVM) is 46.33% for valence states and 48.30% for arousal states. Consequently, the findings have discovered that the new model provides better accuracy compare with the latter one. This is due the fact that feature selection process has been introduced in human emotion recognition model. Hence, feature selection has appeared in this study field as one of essential step in dealing with high dimensionality of feature space problem.

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