Effectiveness of Tuned Q-factor Wavelet Transform in Emotion Recognition among Left-brain Damaged Stroke Patients

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***Abstract* - Emotion recognition is impaired among stroke patients due to brain injury. It has given negative impact towards stroke patients because of the difficulty in expressing themselves. Hence, the vision is to overcome this problem by creating a platform to predict the emotion of stroke patients for them so that recurrent stroke events can be avoided. EelectroEncephaloGraph (EEG) of 19 Left Brain Damage patients (LBD) are used as database. The objective of this paper is to compare the accuracy between Tuned Q-factor Wavelet Transform (TQWT) and Wavelet Packet Transform (WPT). The collected raw EEG signals are de-noised by using 6th order Buttterworth filter. Then, filtered signals were fed into time-frequency analysis tools namely TQWT and WPT to transform the time domain signals into time-frequency domain signals. Hurst exponent feature is extracted from the corresponding time-frequency domain signals before enhancement by using principal component analysis (PCA). Lastly, classification is done through K-nearest neighbour (KNN), probabilistic neural network (PNN) and random forest (RF) in order to evaluate the performance of the recognition system. From the result, it is found that the classification accuracy is consistently higher in TQWT method.**

Keywords - tuned Q-factor Wavelet Transform; wavelet packet transform; hurst exponent; emotion; stroke; left-brain damage

I. INTRODUCTION

Emotion is a psychological state which is mentally linked with thoughts, feelings as well as behaviours. Changes of different emotions is often led by the changes in peripheral physiology itself. Previous studies shown that several approaches have been done in order to perform emotion recognition including speech signal, gestures, facial images and physiological signals [1]. Unlike physiological signals, the other methods are less efficient on detecting the internal emotions realized in the body. Today, the researchers are working on developing intelligent emotion recognition system through physiological signals (Electroencephalogram (EEG), Electromyogram (EMG), Electrocardiogram (ECG), Skin temperature (SK), Photopletysmography (PPG), etc) [2-3].

Stroke (clinically known as cerebrovascular accident (CVA)) is a medical emergency where the supply of blood to the brain is either interrupted or reduced. When this happens, the brain does not get enough oxygen or nutrients, which causes brain cells to die. There are three main kinds of stroke; ischemic, hemorrhagic, and transient ischemic attack. Since ischemic is the most common form of stroke, it is selected to be the main focus in this paper. In May 2014, a statistic showed that stroke deaths in Malaysia is 12.19 % of total deaths [4]. In a recent study where a total of 7668 stroke patients were recruited for analysis, it has been found that Ischemic stroke incidence is estimated to increase annually by 29.5% and hemorrhagic stroke by 18.7%. On average, patients were aged 62.7 years (standard deviation of 12.5). Ischemic stroke accounts for 79.4% of the cohort with a slightly higher proportion of male patients (55%) [5].

In this work, the authors decided to study emotion recognition among left-brain damaged ischemic stroke patients. Two different time-frequency analyses have been chosen here. Comparison was made between TQWT and WPT technique by evaluation of classification accuracy. Introduction was given in the first section of this paper. Then, literature review regarding time-frequency analysis and biomedical signal processing will be presented in the following section. Methodology flow of this work will be explained in detail in the third section. Results and discussion of this work can be seen in the fourth section. Finally, conclusion and future recommendation is also given in the end of this paper.

II. LITERATURE REVIEW

In the area of biomedical signal processing, a lot of methods has been used in order to produce better quality of information through either time domain or frequency domain. Previously, time domain analysis is very common among EEG study where researchers have been using the same six features namely mean, standard deviation of raw signal, mean of absolute value for first difference of raw signal, mean of absolute value for the first difference of normalized signal, mean of absolute value for second difference of raw signal and mean of absolute value for second difference of normalized signal [6]. However, the emotion classification result from Takahashi et al. was only

41.7 % accuracy for 5-class problem. The highest accuracy among time-domain analysis, 86.25 % was found in Li et al. for three-class problem. Other than time domain, frequency domain analysis was also growing very rapidly among signal processing studies. One recent emotion study had used bispectral analysis in order to solve two-class problem and they achieved 61.17 % and 64.84 % for each class [7].

Recently, time-frequency domain has also received much attention from the signal processing research groups. A lot of work has been done with regards of time-frequency techniques. Multi-wavelet Transform (MWT) is another commonly used method of transforming time-domain data into time-frequency domain. A recent emotion classification study managed to achieve 98.10 % by using features extracted from MWT signals for four-class problem [8]. In their study, they extracted features such as mean, standard deviation, variance, Shannon entropy measure, Hjorth parameters, band power. In another emotion study, the classification rate was 84.79 % by using a few features extracted from MWT signals as well [9]. The features they extracted were ratio of norms based measure, Shannon entropy and normalized Renyi entropy measure. Discrete Wavelet Transfrom (DWT) is another method to transform signal into time-frequency domain. A lot of researcher has implemented this method in emotion study. One study has been done on five-class emotion recognition by using DWT which involved a few mother wavelets and they had extracted statistical features such as power, standard deviation, variance and entropy. Even though the features were relatively simple, they managed to achieve 79.18 % accuracy [10]. Daimi and Saha also managed to use another method namely Dual-tree Complex Wavelet Packet Transform with 12 sub-bands for their emotion study. They achieved maximum accuracy of 71.2 % for two-class problem [11]. The most recent paper which is related to the scope of this thesis is written by Mohammadi, Frounchi and Amiri. They achieved 84.05 % and 86.75 % for a two-class problem by implementing DWT using family wavelet 'daubechies 4' and extracting entropy and energy from the transformed signals [12].

III. METHODOLOGY

Fig. 1 shows the complete methodology flow of this research. The database of this study is 14-channel, 128 Hz EEG signals collected from 19 left-brain damaged stroke patients, 19 right-brain damaged stroke patients, and 19 normal control. A series of emotional videos were shown to the participants in order to induce respective emotions (anger, disgust, sad, surprise, happy and fear). The EEG recording device used for this study is Emotiv EPOC. The complete EEG data acquisition process and experiment protocol is described precisely in previous work [13].

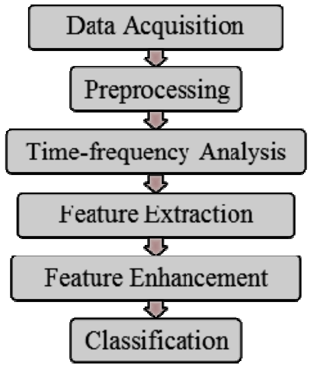

Fig. 1. Methodology flow.

A. *Normalization, Framing and Noise filtering*

Before filtering, EEG signals has to be standardized in order to create the same amplitude range for better comparison purpose. Here, standardization is carried out by the deduction of mean value of input signal and the baseline signal from the original input signal. Next, six equal frames of 7 seconds are segmented from the standardized input signal. Furthermore, the noises and artefacts were removed through 6^{th} order Butterworth band pass filter at the cut-off frequencies of 0.5 Hz and 49 Hz. Since it has been proven that the low frequency band is not significant in emotion prediction task, delta band was not included in the signal processing [14].

B. *Acquiring Time-frequency Domain Sub-bands using Wavelet Packet Transform*

WPT is able to provide different information in a different angle where frequency band localization is made possible. The waveforms are denoted using three parameters which are position, scale and frequency. Signals can be divided into numerous expansions when wavelet packets are used. The reason of using WPT instead of DWT has been explained in detail in previous study [13]. In wavelet packet situation, each detail coefficient vector is further decomposed into two parts. The same approach is used in approximation vector splitting. This step provides the richest analysis where the complete binary tree can be produced [15].

Conventionally, there are five common frequency range in EEG signal. They are delta, theta, alpha, beta, and gamma. However, since delta and theta did not give much emotional information in waking condition, they are removed from the list of frequency bands. Alpha-to-beta and alpha-to-gamma are another two frequency ranges added into the frequency band variation. The purpose of it is to investigate the impact of emotion recognition when a different frequency range is introduced in the analysis. In WPT, the selection of number of decomposition is very important for signal analysis.

Decomposition level is always chosen based on the desired frequency components. The levels chosen are the parts of the signal that contains necessary frequency range and the classification of signal are retained in the wavelet packet coefficients. Each frequency band has different combination of wavelet packets at different decomposition level. The complete detail is presented in Table I. For example, [4 2], 4 indicates the decomposition level, while 2 indicates the second member of that level. Here, decomposition is done up to 6 levels.

In wavelet transform, there is a parameter named wavelet family. Researchers need to decide and select which are the most suitable wavelet type for their study. In this work, since EEG signals is utilized, four wavelet family has been selected: Daubechies 4 (db4), Daubechies 6 (db6), Symlet 8 (sym8) and Coiflet 5 (coif5).

TABLE I. WAVELET PACKETS FOR EACH FREQUENCY BAND.

Frequency band	Frequency range	Wavelet packets	
Alpha	8 – 13 Hz	[4 2]	8 – 12 Hz
		[6 12]	12 – 13 Hz
Beta	13 – 30 Hz	[6 13]	13 – 14 Hz
		[5 7]	14 – 16 Hz
		[3 2]	16 – 24 Hz
		[4 6]	24 – 28 Hz
		[5 14]	28 – 30 Hz
Gamma	30 – 49 Hz	[5 15]	30 – 32 Hz
		[2 2]	32 – 48 Hz
		[6 48]	48 – 50 Hz
Alpha-to-Beta	8 – 30 Hz	Alpha and beta combined	
Alpha-to-Gamma	30 – 49 Hz	Alpha, beta and gamma combined	

C. *Acquiring Time-frequency Domain Sub-bands using Tunable-Q factor Wavelet Transform (TQWT)*

TQWT is innovated by Ivan Selesnick in year 2011. According to his reports, it is a flexible and fully discrete wavelet transform (DWT) that is tailored for the investigations of oscillatory signals [16]. By adjusting its input parameters, Q-factor Q, rate of over-sampling or redundancy r, and number of levels of decomposition J, flexibility is achievable in the analysis.

The selection of parameters in TQWT has to be done accordingly. After referring to previous works [16,18], the final decision is described as below:

(i) Q-factor: The signals of interest here is EEG signal in alpha, beta, gamma, alpha-to-gamma and beta-to-gamma band. So, to tune the TQWT wavelet toward EEG band, a Q-value that corresponds to the EEG signal in emotion study is selected. To tune the wavelet toward the signal, Q = 1 is chosen, as this provided a wavelet that closely models the shape of a Mexican Hat wavelet family.

(ii) Maximum number of levels (J_{max}): In this study, the maximum level J is 11. Hence, a total of 12 sub-bands including one low pass sub-band are considered in this work.

(iii) Redundancy parameter (r): The specific value r = 3 has been previously recommended when processing biomedical signals [16,17]. Hence, redundancy parameter r, 3 is selected throughout the analysis in this work. Since Q = 1 and r = 3, the α and β scaling values are 1 and 0.667 respectively.

D. *Hurst Exponent*

After the time-frequency analysis, chaotic behaviour and non-linearity of the EEG signals is studied by extracting Hurst Exponent. As a measure of persistence, Hurst exponent is commonly used to predict changes in a time series. This method is very efficient for long range memory because of the index of dependence property. The quantification created from hurst exponent is able to reveal the regression tendency of a time series [19]. The range of H value is between 0 and 1 ($0 \leq H \leq 1$). If H is in the range of $0.5 < H < 1$, the time series is considered positively correlated or persistent. Inversely, if the range is $0 < H < 0.5$, it indicates anti-correlated time series (anti-persistent).

E. *Feature Enhancement*

In order to improve the accuracy of the classification between six emotions which is a rather difficult classification problem, Principle Component Analysis (PCA) is implemented here. PCA is a useful tool for data analysis where patterns can be identified from the data. In fact, data can be expressed in a way that similarities and differences can be highlighted. According to Smith, PCA is a powerful tool for analyzing data since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available [20]. PCA acts as a pre-processor in the emotion classification stage where the features are transformed into principle component scores before they were put into training and testing. This step is important in order to increase the classification accuracy rate.

F. *Classification*

In classification stage, three different types of classifiers are chosen in order to train and test the input features that are applied here. Two types of classification are carried out throughout this stage, namely six emotion classification which involves six discrete emotions (sad, anger, disgust, fear, surprise and happy).

1) *K-Nearest Neighbour*

KNN is a non-linear, supervised learning algorithm and a simple classification model that makes use of lazy learning [23]. Its' operation is driven based on data where an unknown point is pre-assigned to the predominant class within the k nearest known points belonging to the training class. In other words, emotions are determined by a majority vote of its nearest neighbours since they are assigned based on the most common class amongst its k nearest neighbours. The value of *k* is chosen in accordance to the number of classes. In classification application, as the *k* value increases, the effect of noisy data among training samples reduces. In this work, Euclidean distance is used for KNN classification method. Here, the *k*-value is varied from 1 to 10. For each case, best *k*-value is chosen according to the classification accuracy.

2) Probabilistic Neural Network

PNN, which was first introduced by Donald F. Specht in 1990, is founded on the Bayesian classification theory and the approximation of Probability Density Function (PDF). Essentially, the nonlinear decision boundaries, which approximate the Bayes optimal are calculated by means of PNN. Bayes optimal is formed by sigmoid activation function which is substituted by an exponential function, hence, PNN has fast computation time [22]. In this work, three sets of training and testing ratio are used: 50 % training: 50 % testing, 60 % training: 40 % testing and 70 % training: 30 % testing. Spread value of 0.1 to 2.0 with the increment of 0.1 is selected for testing.

3) Random Forest

Another method used in classification stage is Random Forest (RF), which is a very efficient algorithm in ensemble learning. Created by Leo Breiman, RF has shown remarkable results in classification problems [23-25]. An ensemble of classification trees which are built on bootstrap sample of data is utilized by combining bagging and random variable selection. At each split, variable candidate set is randomly chosen from the whole variable set. At this stage, randomness is introduced when different random subsamples are grown on each tree. In order to ensure low-bias environment, each tree has to be fully grown. Other than that, low correlation for each tree has been made possible by implementing bagging and random variable selection. Through the averaging over a large ensemble of low-bias, high-variance but low correlation trees, the algorithm yields an ensemble forest [23]. Similar to KNN and PNN, the accuracy result for different number of grown tress, Ntree in RF classifier were determined in advance and is reported in Section 4. In this work, three sets of training and testing ratio are used: 50 % training: 50 % testing, 60 % training: 40 % testing and 70 % training: 30 % testing. Ntree used here is between 105 to 150 with the increment of 5 bags. M_{try} is defaultly set as 4, which is the square root of 14 EEG channels.

IV. RESULTS AND DISCUSSION

In this section, time-frequency signal of and WPT TQWT are shown in the beginning, followed by the selected parameters for each feature. After that, classification accuracies are presented and discussion is done in the end of the section.

A. Wavelet Packet Transform

In order to obtain the desired frequency band, decomposition is done before wavelet coefficients are extracted. Each desired frequency band is the combination of a few coefficients just as described in Table I. The example given here is data sample from RBD patient # 1, anger emotion Trail # 1, Frame # 1, Channel #1 (128 Hz × 7 s = 896 data point). The time domain EEG signal is different from time-frequency domain EEG signals which are extracted using WPT method with mother wavelet of 'db6'. The length of wavelet coefficients changed along with the level of decomposition. As the decomposition level gets deeper, the wavelet coefficients become lesser.

B. Tuned Q-Factor Wavelet Transform

For this method, frequency localization for each EEG frequency band is done beforehand through the cut-off frequencies during Butterworth 6th order filtration technique. There is no need to find the desired wavelet coefficient in TQWT method. In this work, the maximum decomposition level is 11. In the end, 12 sub-bands are produced just as described in Section 3C. However, after data validation is done through ANOVA, it is found that sub-band # 7 until sub-band # 12 is not significant. Hence, they are excluded from further analysis. The more the decomposition level, the shorter the sub-band is. Sub-band 1 is the result from first level decomposition. Hence, the data point is 1024.

C. Parameter Selection for Comparison Purpose

In order to conclude this results for further discussion, the most suitable method is chosen based on the maximum average accuracy for each feature type in each classification method. Table II shows the optimum k-value for KNN classifier, optimum spread factor for PNN classifier and optimum number of trees for RF classifier. It is also found that the best EEG frequency band for both feature type is gamma band. Meanwhile, the best wavelet family for WPT method is db6 and the best sub-band for TQWT method is sub-band 5.

TABLE II. SELECTED PARAMETERS IN EACH FEATURE TYPE.

Feature Type	k-value	spread factor	trees	Frequency Band	Wavelet family
Hurst WPT	7	0.16	125	γ	db6
Hurst TQWT	9	0.18	150	γ	Sub-band 5

D. Classification Performance

For Hurst WPT feature, the maximum averaged accuracy is found in PNN classifier as well where LBD achieved 29.52 %, which is only slightly higher than KNN and RF classifier. According to Fig. 2, from PNN classifier, the most sensitive emotion in LBD group is surprise (30.83 %), while the least sensitive emotion is disgust (27.84 %). However, there is no huge difference in terms of sensitivity between emotions. In short, through Hurst WPT feature, LBD has shown low sensitivity towards all six emotions, which led to low average classification accuracy.

In Hurst TQWT, there are not much difference between the three types of classifier. However, numerically, the most contributing classifier is KNN, with the accuracy of 47.61 %. As shown in Fig. 3, from KNN classifier, the most sensitive emotion in LBD group is happy while the least sensitive one is surprise emotion.

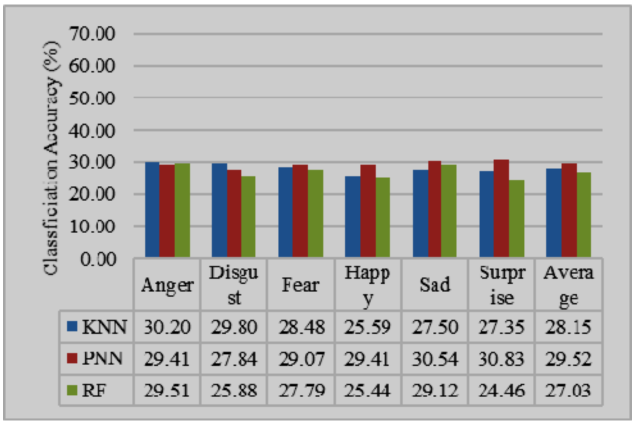

Fig. 2. Emotion classification performance for Hurst WPT feature.

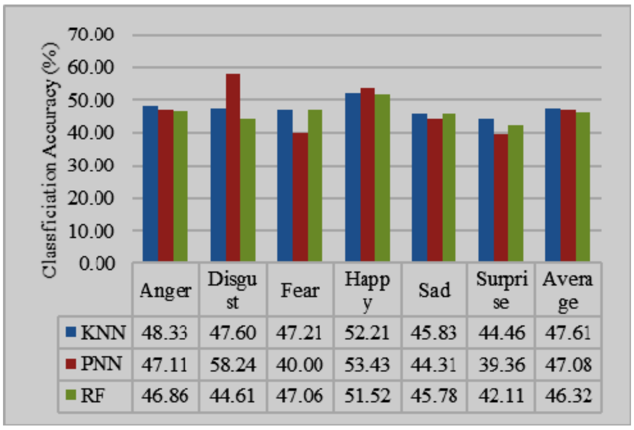

Fig. 3. Emotion classification performance for Hurst TQWT feature.

Due to the irregularity of signal in emotion inducement, the correlation of EEG signal within the class is not suitable in emotion recognition. The performance of Hurst WPT and Hurst TQWT here has showed very poor capability in recognizing its own class. The averaged classification accuracy is ranged only between 27 % – 47 % even after feature enhancement process. This means that there is too much variation within the class itself that leads to poor recognition ability. The value of correlation exponent seemed to be high in one moment and low in the other, causing too much fluctuation within the class. This pattern happened in all six emotions and caused high similarity between them. Hence, there is very low significance value in these features. This is supported by ANOVA, where most of the p-values are larger than 0.05 in all type of wavelet families and frequency band combinations. However, there is some promise in TQWT-based feature as the averaged classification accuracy of Hurst TQWT here is at least 20 % higher than WPT-based feature.

By adjusting its input parameters, Q-factor Q, rate of over-sampling or redundancy r, and number of levels of decomposition J, flexibility is achievable in the analysis. This advantage enabled the system to create a waveform that can match with EEG signal the most. Hence, the features from TQWT has contributed to better classification accuracy.

V. CONCLUSION

In conclusion, by comparing Hurst WPT with Hurst TQWT, Hurst TQWT is more efficient in giving higher average classification accuracy. In the future, it is recommended to use TQWT-based features for EEG-based emotion classification purpose. For instance, implementation of ontology research by including TQWT method in order to create a more versatile and accurate emotion recognition system which not only involves EEG signal processing module but also the facial image processing module. Furthermore, high flexibility of TQWT is useful for all types of signal processing analysis, by adjusting the parameters in order to suit each application.

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