Article

Continuous m-Health Monitoring and Patient Verification Using Bioelectrical Signals

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Abstract: The World Health Organization(WHO) in 2016 considered mHealth as: "the use of mobile wireless technologies including smart devices such as smartphones and smartwatches for public health" as an important resource for health services delivery and public health given their ease of use, broad reach and acceptance. WHO emphasizes the potential of this technology to increase access to health information, services and skills as well as promoting positive changes in health behaviors and management of diseases. In this regard, the capability of smartphones and smartwatches for m-health monitoring as well as verification of the patient the signal has become an important component of mHealth system. Most of the smartwatches could extract more than one bioelectrical signal therefore, therefore they provide suitable platform for extracting health data for e-monitoring. The existing approaches have not considered the integrity of data obtained from these smart devices. Therefore, it is important that the integrity of the collected data be verified continuously through user authentication. This could be done using any of the bioelectrical signals extracted and transmitted for e-monitoring. In this article, a smartwatch is used for extracting bioelectrical signal before decomposing the signal into sub-bands of Detail and Approximation Coefficient for user authentication. To select suitable features using biorthogonal wavelet decomposition of signal from a non-intrusive extraction, a detailed experiment is conducted extracting suitable statistical features from the bioelectrical signal from 30 subjects using different biorthogonal wavelet family. Ten features are extracted using Biorthogonal wavelet to decompose the signal into three levels of sub-band Detail and Approximation Coefficient and features extracted from each level the decomposed Detail and Approximation Coefficients. Comparison analysis is done after the classification of the extracted features based on the Equal Error Rate (EER). Using Neural Network (NN) classifier, Biorthogonal Wavelet Detail Coefficient Sub-band level 3 of bior1.1 achieved the best result of EER 13.80% with the fusion of the best sub-band three levels of bior1.1 achieving a better result of 12.42% EER.

Keywords: bioelectrical signals; biorthogonal wavelet; approximation coefficients; detail coefficient; wavelet transform; smartwatch; m-health Monitoring

1. Introduction

The use of smartphones has increased over the years with many services adapting to mobile applications. The growth has seen competition in the use of mobile applications to market and advertise goods and services. This has increased investment in the provision of services using apps on mobile devices. This is because it will be more convenient to access the services on mobile devices compared to traditional computing sets. It is estimated that the worldwide usage of the most popular mobile device, mobile phones, is expected to reach an estimated 5 billion by 2019 [1].

The statistic states that a total of 2.1 billion of the 4.77 billion phones are smartphones. Smart devices are valuable devices not only because of its sophistication but also because they are used to store sensitive information like health, business and financial information etc. [2]. Also, most social network applications such as Facebook, WhatsApp etc. can be accessed once the device is accessed. Therefore, it is expedient to secure these mobile devices to prevent access by an unauthorized user. Knowledge based authentication mechanism have been a traditional way for authenticating a user's access to a device. The use of knowledge-based user authentication to secure mobile devices has been effective but limited. The use of secret information known to the user can be forgotten or can be obtained by another person if written down [3]. To improve on the limitation of knowledge base user authentication on a mobile device, biometrics for user authentication is becoming prevalent. Recent researches are focusing more on the use continuous and transparent biometric user authentication for securing smart mobile devices [4]. Smartwatches are among the smart devices that are becoming popular because of the incorporation of more sensors. The increase in their technological advancement has enhanced their functionality and capabilities. For example, some have the capability of accepting and declining calls, reading Short Message Service (SMS), listening to music, navigation etc. Smartwatches of recent has the capability for user authentication enhancement for mobile devices. They can create activity logs, extract bioelectrical signals, context awareness data and transmit same to a mobile device [5, 6]. To implement a biometric user authentication mechanism on a mobile smart device, suitable features are essential for the implementation. As stated earlier, WHO emphasizes the potential m-health technology by delivery of Cluster of Health Systems and Innovation [7]. Mobile device and application have integrated into the health system with telemedicine and telehealth via the Internet of Things (IoT) [8]. Mobile and wearable devices are useful for health and wellbeing monitoring to improve and authenticate the patient for data trust. Therefore, the evaluation of features extracted from the smartwatch is also imperative. In this paper, a smartwatch is used to extract bioelectrical signal while decomposition of the signal is done using Biorthogonal Wavelet. The signal is extracted for mobile health monitoring and verifying the patient from which the health information is extracted from.

Several techniques have been used for feature extraction including wavelet transform. Wavelet transform is widely used for the extraction of non-stationary bioelectrical signal features [9]. Wavelet transform is classified into two types, Continuous Wavelet Transform (CWT) and discrete Wavelet Transform (DWT). Discrete wavelet transform is popular for measurement and analysis of time-frequency and spectral component variation [10, 11]. The method has been used extensively [12], Subasi [13] and Jahankhani [14]. The use of DWT enables the extraction of features that vary in time and is useful for analyzing transient signals [15, 16]. There are several types of DWT which include Biorthogonal, Morlet, Symlets, Mexican Hat, Haar, Daubechies, Coiflets, Meyer [15, 18] as shown in Figure 1. The Biorthogonal wavelet family includes Bior1.1, 1.3, 1.5, Bior2.2, 2.4, 2.6, 2.8, Bior3.1, 3.3, 3.5, 3.7, 3.9, Bior4.4, Bior5.5 and Bior6.8. Biorthogonal wavelet transforms decompose a signal into Approximation and Detail Coefficients. The Approximation and Detail Coefficients contains relevant information of the signal from which features can be extracted. Each n-level of the sub-band further decomposes the bioelectrical signal into a high and low frequency signal component [15, 19].

Several literatures have shown that bioelectrical signals contain noise therefore require pre-processing. The application of biorthogonal wavelet filters some of the noise in bioelectrical signals because biorthogonal wavelet uses a filter bank when decomposing the signal into sub-bands. The overall aim of this work is focused on the performance of biorthogonal wavelets features by applying the most suitable sub-band of either Approximation Coefficients or Detail Coefficients features for classification. Majority of the prior work using Biorthogonal wavelet [20-26] used either Approximation Coefficients or Detail Coefficients mostly from signal extracted using intrusive method. The used of smartwatch reduces the intrusiveness in the extraction of the signal therefore; a comparison analysis is carried to determine the most efficient of the Biorthogonal wavelet family for extracting features. The most efficient coefficient could be used to implement user authentication mechanism for m-health monitoring. It is important to note that mobile health is on the rise and useful for daily life related health monitoring of patient however, most are for emphases on the usability [7, 27] and availability of the health data. The authenticity of the data should be verity because the wearable device could be worn by a different person other than the patient. The work proposed a framework design for implementing a m-health monitoring as well as verity the patient the health information is coming from. The monitoring framework should be able alert the staff when a different person's information instead of the patient. The framework includes a transparent data extraction, pre-processing, feature extraction and classification for the patent's verification. The feature extraction and processing are important due to mobile device power processing capability. The most viable section of the signal should be identified for feature extraction for patient authentication.

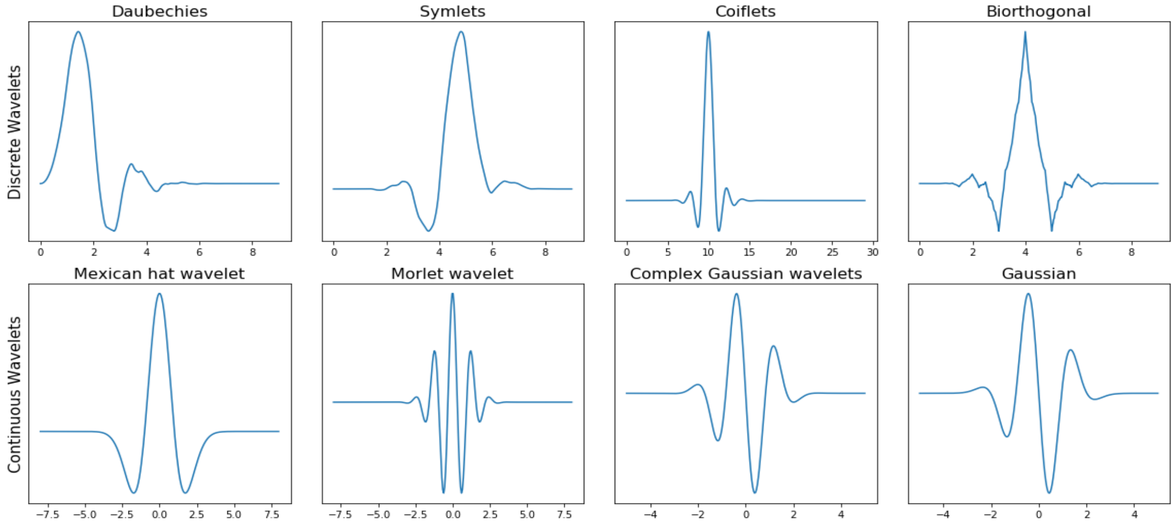

Figure 1.Wavelets families with the first row showing discrete wavelets and the second row showing several continuous wavelets

2. Methodology

2.1. Data Collection

To apply a robust dataset, 30 subjects are used for the evaluation of the statistical feature and the comparison experiment using different biorthogonal wavelet family. Using a smartwatch, bioelectrical signals of the heart rate is extracted for one hour without a specific task. The data is transmitted to a smart phone for storage via a Bluetooth connection. A sampling rate of 8 samples per second is used to extract enough data points per second. The signal is then segmented into a time frame of 10 seconds. A total of 360 data segments containing 80 data points per segment are used per subject for feature extraction. Before the evaluation of the biorthogonal wavelet sub-bands, 12 subjects are used to select the most suitable features before applying same to 30 subjects. Figure 2 show the applications used for the extraction the data from the smartwatch to the smart phone. The different android applications in the phone perform different function the continuously extract the dataset if the two devices and within a communication distance. Within the smart phone as shown in Figure 3, the AutoStart and staY application search for the pair blue tooth device and reconnects it whenever it's found. This enables the smartwatch and the smartphone to reconnect, pair up and enable data transfer when the smart or phone is switched on. The Microsoft health is a proprietary application customized to communicate with the inbuilt application on the smartwatch. The third application, Companion for Band bind with the Microsoft health to log its data in a better and more presentable.

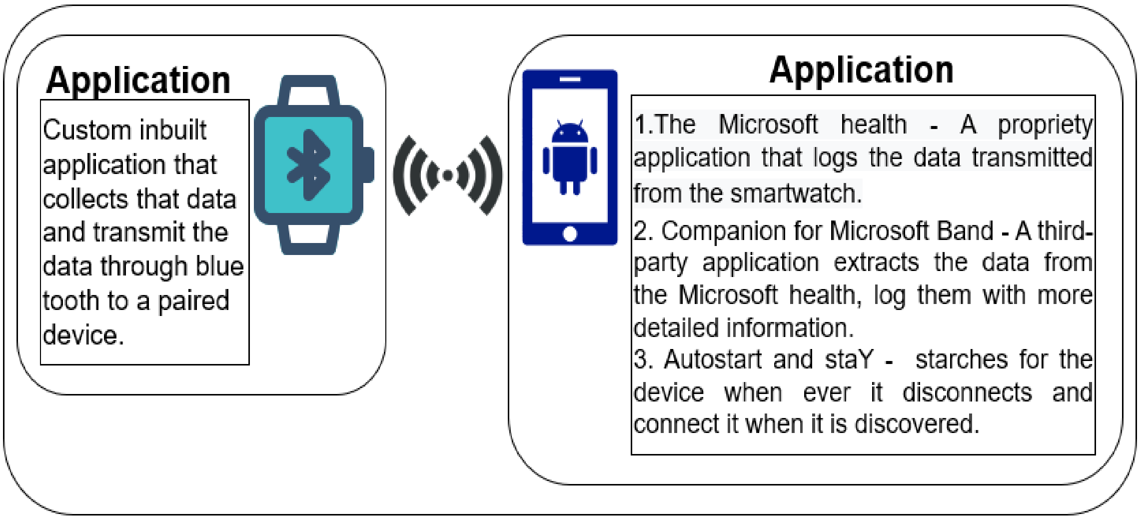

Figure 2. A high-level view of the system used, comprising a Smartwatch and Smartwatch.

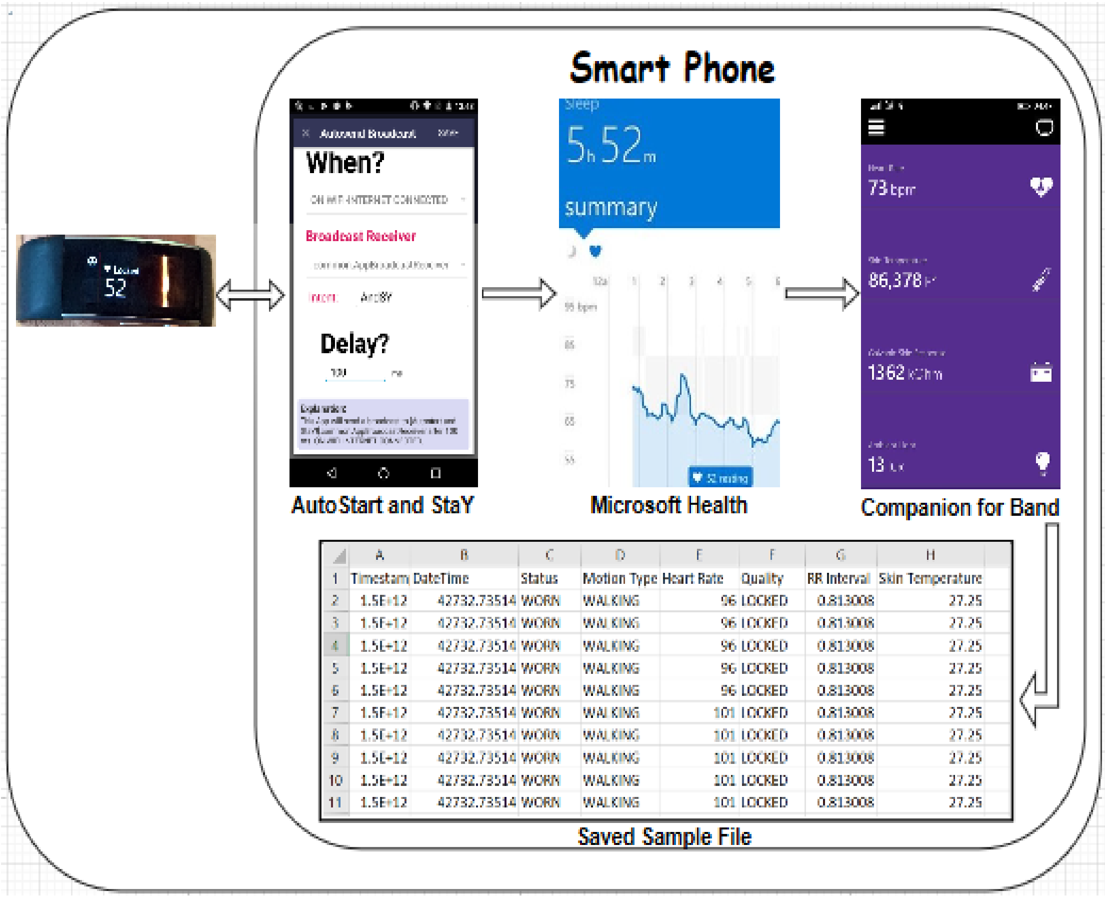

Figure 3. Illustration of the Mobile Application process within the Smartphone

2.2. Biorthogonal Wavelet Decomposition

The signal processing involves the reduction of the noise using filters. Biorthogonal wavelet processes a signal using of low pass (L) and high pass (H) filters. The output is either a decomposition or reconstruction of the signal of the low pass or high pass filters into four different outputs:

- Decomposition low-pass filter = Lo_D
- Decomposition high-pass filter = Hi_D

- Reconstruction low-pass filter = Lo_R
- Reconstruction high-pass filter = Hi_R

This work applies the decomposition of the signal using the high and low pass filters to the n numbers of feature samples generated. The wavelet decomposition low-pass filter $[h_n]$, the lowest level of the transform and decomposition high-pass filter $[g_n]$ the highest level of the transform. The output is the approximation (A_i) and detailed (D_i) coefficients. The coefficient of each signal sample frequency of the wavelet is calculated. To determine the ith level, the following formula is used (28):

$$\text{Approx. coefficient } (A_i) = \frac{1}{\sqrt{M}} \sum_n x(n).\psi_{j,k}(n) \tag{1}$$

$$\text{Detail coefficient } (D_i) = \frac{1}{\sqrt{M}} \sum_n x(n).\varphi_{j,k}(n) \tag{2}$$

The low and high pass filter rely on $\varphi_{j,k}(n)$, the scaling function and $\psi_{j,k}(n)$, the wavelet function while the signal length is M.

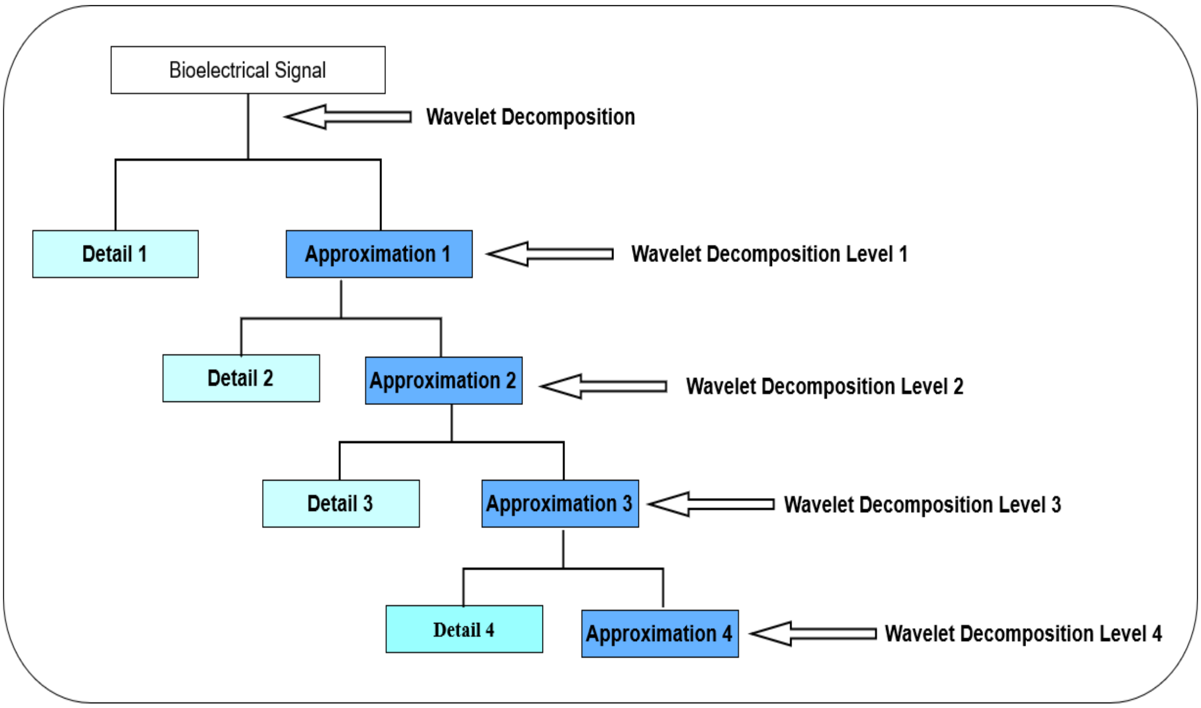

Figure 4. Wavelet decomposition of the detail and approximation coefficients

2.3. Feature Extraction

The first step in the process is identifying the features to use. Based upon prior works on bioelectrical feature extraction, statistical feature has been employed [13, 26, 29]. An initial 12 subjects are used to test run the 12 statistical features applied to 4 sub-bands. The 12 statistical features are later extracted from the biorthogonal wavelet 3 sub-bands of 30 subjects. The feature used in this experiment are listed as:

Table 1. Showing the Features extracted

	Feature Set	Feature description	Feature Formula
1	Variance	This is the sum of square distance of the bioelectrical signal.	$variance = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)$
2	Mean of the energy	The signal mean of the energy is the energy average value of the bioelectrical signal.	$E = \frac{\sum_r \exp(-\beta E_r) E_r}{\sum_r \exp(-\beta E_r)}$
3	Minimum Energy	This is the lowest energy value of the bioelectrical signal	$\text{Min. Amp.} = \text{Minimum Signal Energy}$
4	Maximum Energy	This is the highest energy value of the bioelectrical signal.	$\text{Max. Amp.} = \text{Maximum Signal Energy}$
5	Mean	These are the values diversity of the data around the median.	$mean = \frac{1}{n}\sum_{i=1}^{n} x_i$
6	Minimum Amplitude	This is the lowest point from the equilibrium point of the bioelectrical signal.	$\text{Min. Amp.} = \text{Minimum displacement}$
7	Standard Deviation (STD)	This is the square root of the variance of a random variation.	$STD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}$
8	Maximum Amplitude	This is the highest point from the equilibrium point of the bioelectrical signal.	$\text{Max. Amp.} = \text{Maximum displacement}$
9	Range	This is the difference between the highest signal value and the lowest signal value.	Range = max. signal-min. signal
10	Peak2peak	This is the difference between the maximum and minimum values of the bioelectrical signal	P2P= Signal Maximum-to-minimum difference
12	Root Mean Square (RMS)	The RMS is the measurement of the magnitude of a set values within the signal.	$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{N} X_i^2}$

The features are extracted from the detailed (D_i) and approximation (A_i) coefficients as shown in Figure 5. The 12 features are extracted from each level of the decomposed signal of detail (D1-D4) and approximation (A1-A2). 12 features extracted from each of the 3 sub-band levels and classified using Neural Network Feedforward.

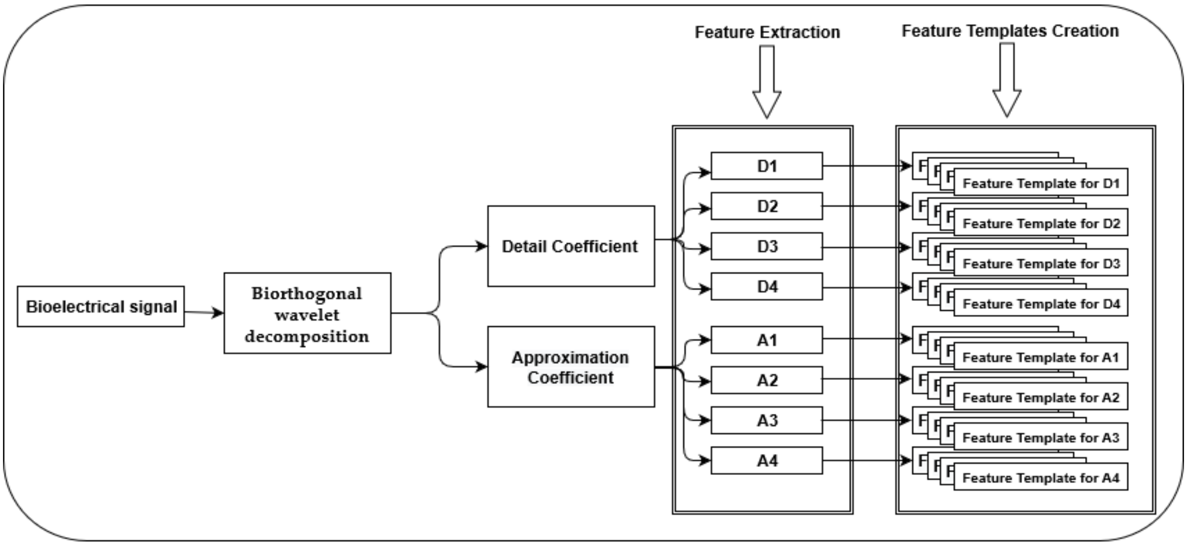

Figure 5. Schematic illustration of the feature extraction process

2.4. Classification

Neural network is one of the most widely used classifier in bioelectrical signal classification. Prior works have used Neural Network for classification of bioelectrical signals [13, 26, 29, 30]. Neural Network can easily map a set of input signals to the output signals [31]. The classification evaluation metric calculates the equal error rate (EER) using false acceptance rate (FAR) and false rejection rate (FRR). The EER is the point at which the FAR and FRR meet. The features extracted from the level 1 to 3 sub-bands of the decomposed signals are classified from each of the biorthogonal wavelet family. The 12 (N) features are sent as input with 75 (M) hidden layers used for the classification. The output is either True Negative (0) or True Positive (1) as shown in Figure 6, while the True Positive indicates as the right patient information while True Negative indicates as non-patient information.

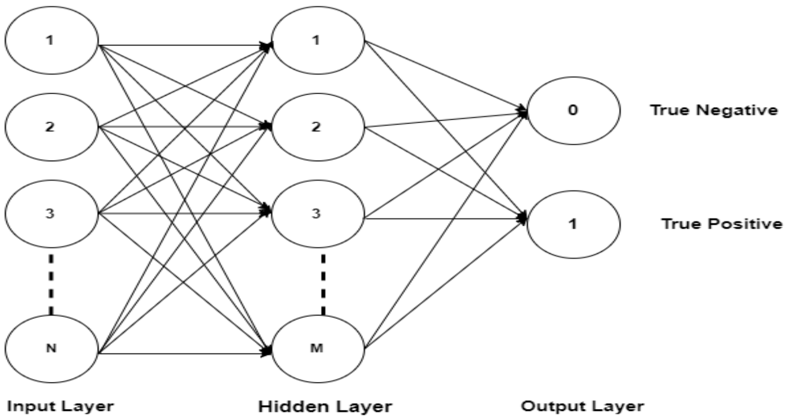

Figure 6. The structure of the Feedforward model used in the study

3. Results

3.1. Result on Selecting the Statistical Features

To study the discrepancy between subjects using the features, the fourteen features are extracted from a segment of the bioelectrical signal. The output is tabulated to show the variations of the features across subjects. The feature variations are important in choosing the most effective features to apply on the biorthogonal wavelet sub-bands decomposition before classifying the output. The graphical representations of the extracted features in Figure 1 to 4 are represented in different feature score ranges. The feature variations are important in choosing the most effective features for classification of subjects. Fourteen statistical features are extracted from the 12 subjects. The features are extracted with MATLAB using the first level detail coefficient of biorthogonal wavelet transform sub-band. The output is tabulated to show the variations as illustrated in Figure 7-10. The feature selection plotting is divided based on the various feature scoring values. The x axis shows the different features scores while the Y axis shows the scores. The disparity of score between the subjects shows good discriminatory information in the features. For example, Figure 7 shows subject 11 and 12 having different score of variances mean of energy and mean and for each subject their feature scores are also different too. This is important as it is used to differentiate the subjects because of the different information provided by the features associated with each subject.

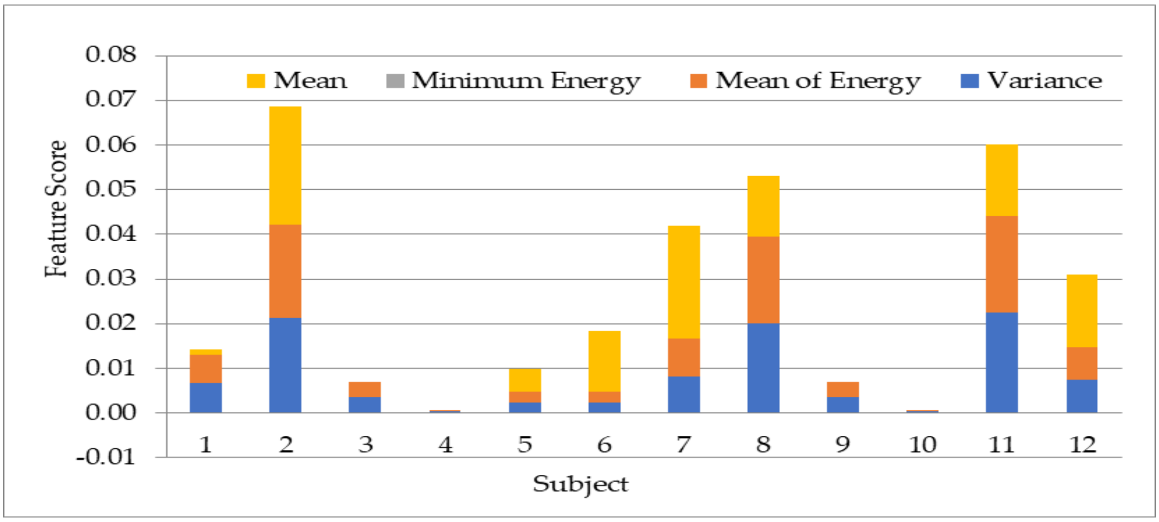

Figure 7. Variation of Variance, mean of the energy, Minimum Energy and mean on twelve subjects

Figure 8 values ranges from 0.0 to 0.03 with the mean having the highest value. The graphical representation shows that the variation of Variance and Mean of the energy provides good value to discriminate subjects with Minimum Energy not having any value. The mean has value for some but not all the subjects. Therefore, the Minimum Energy and the mean will not be ideal for use to classification of subjects. The variation of subjects by the Minimum Amplitude, Maximum energy, and Deviation as illustrated in Figure 2 with values ranging from -0.29 to 0.23 provides for used discrimination, therefore the three will be selected for further feature extraction.

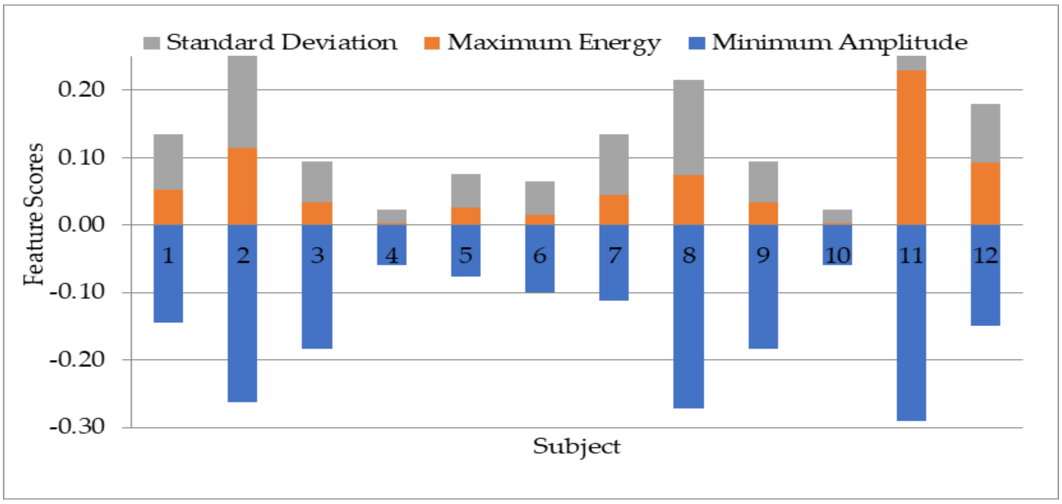

Figure 8. Variation of Minimum Amplitude, Maximum energy, and Standard Deviation on twelve subjects

Figure 9 showing the plot for variation of Maximum Amplitude, Range, Peak2peak and Peak Magnitude shows the Range and Peak2peak scoring the same value across all the subjects while the rest of the features shows good discrimination between subjects. All the features are selected except the Range and Peak2peak. The range is chosen as the use of the two features of Range and Peak2peak will not add value the process since they represent the same value. The variations of all features in Figure 10 except the Average frequency have good values for discrimination. The Mid frequency and Root Mean Square will be selected while the Average frequency will be rejected for the feature extraction process for the 12 subjects. From the fourteen features, ten features of the variance, minimum amplitude, maximum energy, standard deviation, maximum amplitude, peak2peak, peak magnitude to RMS ratio, average frequency, root mean square (RMS) and peak magnitude were chosen.

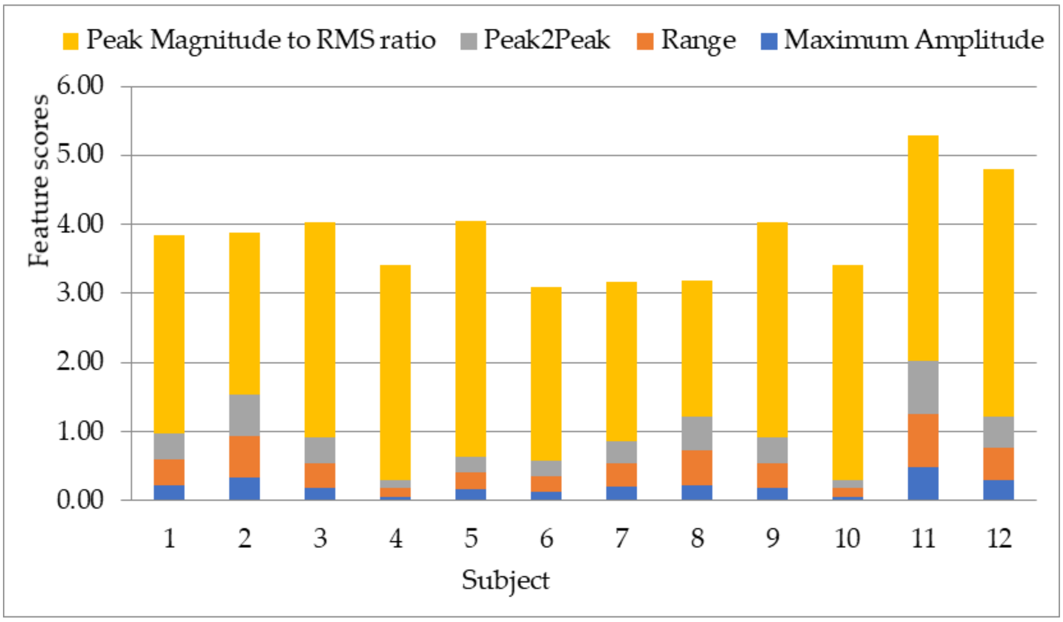

Figure 9. Variation of Maximum Amplitude, Range, Peak2peak and Peak Magnitude on twelve subjects

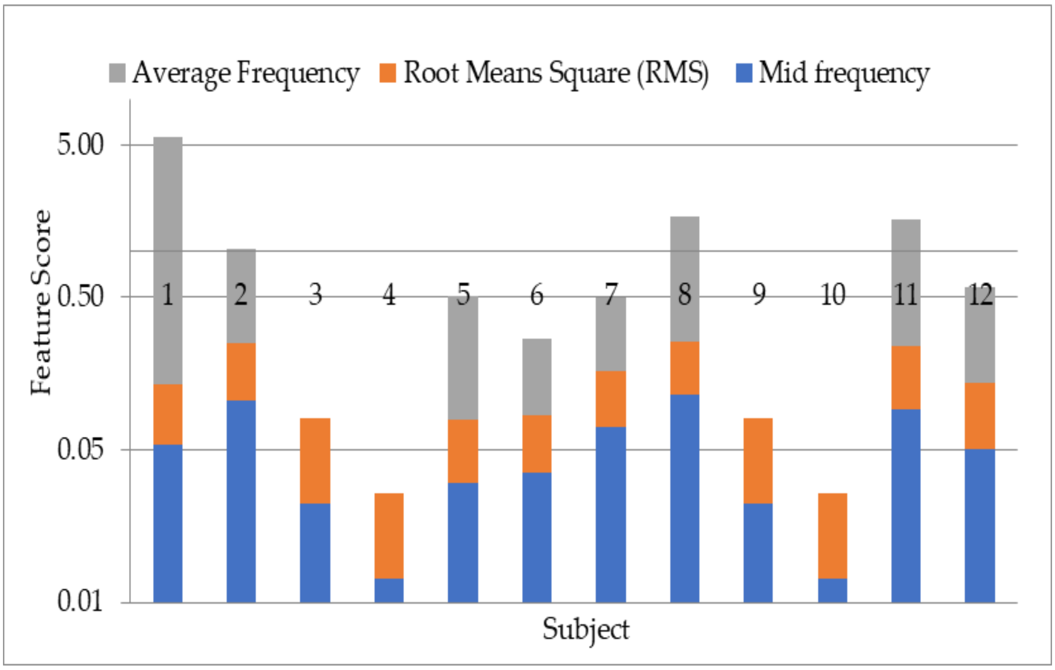

Figure 10. Variation of Mid frequency, Root Mean Square and Average frequency on twelve subjects

3.2. Result on single Sub-band Feature

To extract features from the signal, fifteen different wavelets from Biorthogonal Wavelet family are used to decompose the signal into three sub-bands. To evaluate the performance of the three sub-bands of Approximation Coefficients and Detail Coefficients, the ten features selected are applied to three sub-bands of approximation of coefficients and detail coefficients from 30 subjects. The used of 3 sub-band (decomposition level) is because of the bioelectrical signal frequency of the heart rate. This is necessary because it should correlate with the frequencies necessary for classification [28]. Neural network classifier is used with the same network size across all the sub-bands. The network size is not the best that can be applied but for equal evaluation across the sub-bands, network size 20 is used. Table 1 shows the output result for the sub-bands. To analyse Table 2, two sets of results are presented in a diagram as illustrated in Figure 5 and 6. In these two sets of diagram, radar chart is used to show the fifteen biorthogonal wavet family.

Table 2.The three sub-band levels of approximation of coefficients and detail coefficients (A1: Approximation of coefficient sub-band1, A2: Approximation of coefficient sub-band 2, A3: Detail coefficient sub-band 3, D1: Detail coefficients sub-band1, D2: Detail

No	Wavelet Family	Approx. of Coefficients and Detail Coefficients (%)					
		D1	A1	D2	A2	D3	A3
1	Bior1.1	32.27	31.54	32.21	32.31	16.41	16.66
2	Bior1.3	31.02	31.77	33.51	29.80	16.79	16.56
3	Bior1.5	32.33	31.42	33.32	33.21	17.56	17.20
4	Bior2.2	31.79	31.12	34.50	32.99	20.69	21.69
5	Bior2.4	32.59	31.55	32.06	31.87	20.02	20.95
6	Bior2.6	30.87	31.44	32.32	34.55	21.47	19.94
7	Bior2.8	30.83	30.39	32.66	29.81	20.79	20.44
8	Bior3.1	32.16	31.40	33.67	31.58	29.82	29.70
9	Bior3.3	31.10	33.64	33.74	32.18	32.82	31.90
10	Bior3.5	32.65	31.40	34.44	31.63	31.11	34.32
11	Bior3.7	32.73	32.90	30.08	33.67	28.52	28.95
12	Bior3.9	33.41	29.99	33.10	31.81	28.50	30.67
13	Bior4.4	31.85	29.03	37.57	34.86	36.54	37.16
14	Bior5.5	31.61	31.87	33.67	34.05	35.93	39.01
15	Bior6.8	35.22	33.07	33.59	30.94	37.40	37.90

Figure 11 shows detail comparison of the classification results using the fifteen biorthogonal wavelet decomposition of approximation between sub-band 1, 2 and 3. The results from the two classifications (Figure 11 and 12) produced identical results for the approximation of coefficients and detail coefficients. However, a closer look at the radar chat show the Approximation of coefficient and detail coefficient sub-band results of sub-band 2 and 3 fluttered with in the EER of 30% to 35%. The 3 sub-band showed better performance in the first 7 biorthogonal wavelet for both the approximation of coefficients and detail coefficients.

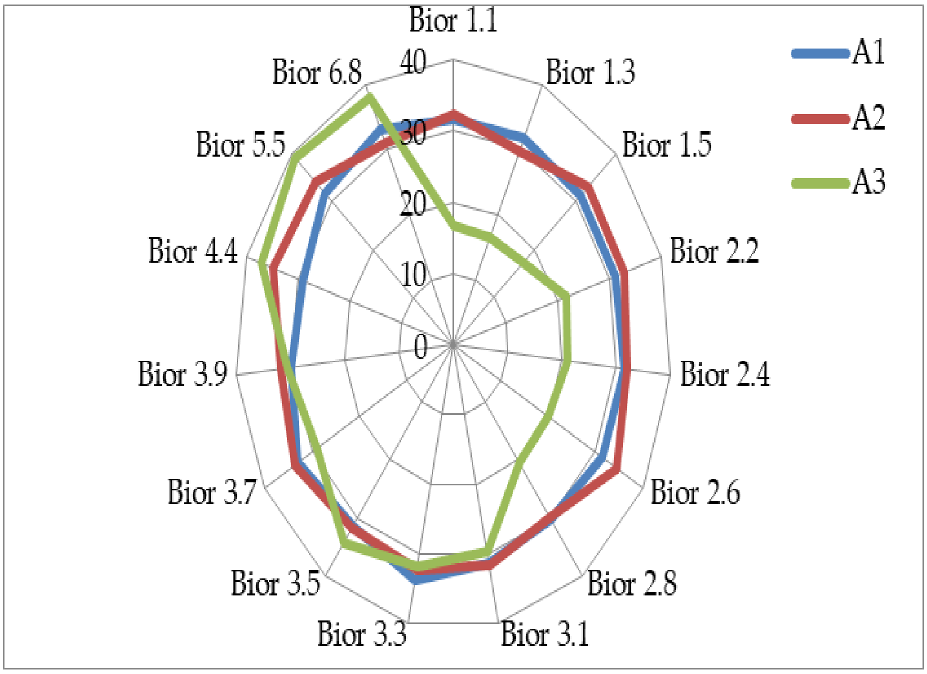

Figure 11. Classification accuracy comparison in EER across various biorthogonal decomposition of approximation of coefficient features (A1: Approximation of coefficient sub-band1, A2: Approximation of coefficient sub-band 2, A3: Approximation of coefficient sub-b)

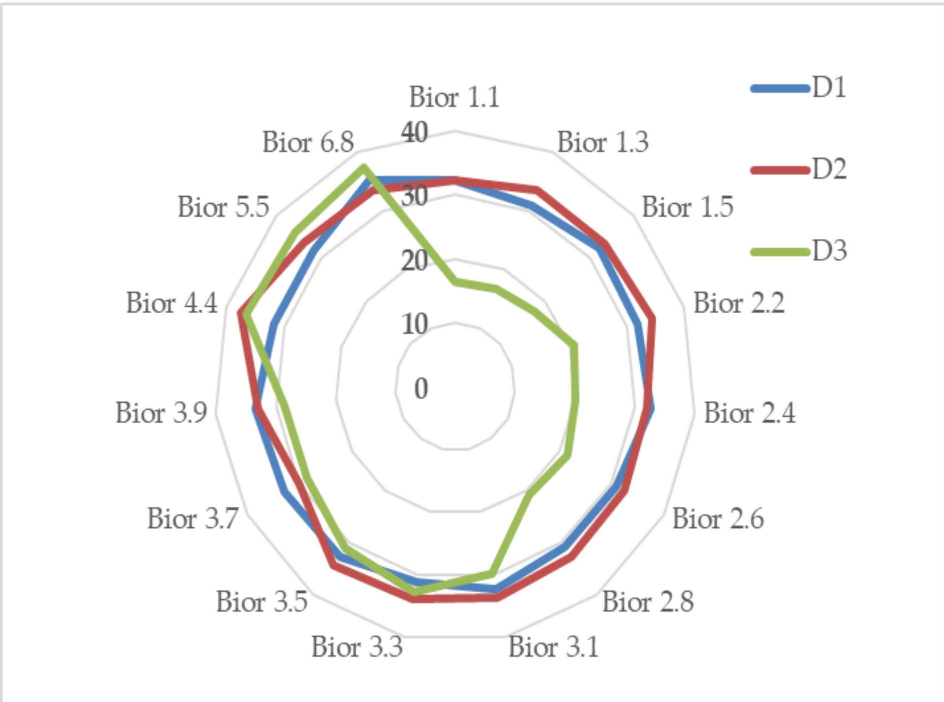

Figure 12. Classification accuracy comparison across various biorthogonal decomposition Detail coefficient features (D1: Detail coefficients sub-band1, D2: Detail coefficients sub-band 2, D3: Detail coefficients sub-band 3)

To further analyze the three sub-band levels of Approximation Coefficients as illustrated in Figure 11, it is of interest to note that the sub-band 1 of the Approximation Coefficients seem to be consistent and within the region of EER of 30% to 35% except in bior4.4 where it is below EER of 30%. This implies that using the bior4.4 will produce almost the same result irrespective of the

Biorthogonal Wavelet family used if it is suitable for the feature extraction of the dataset. The Detail Coefficient features of sub-band 1(D1) in Figure 12 shows the same pattern at the approximation of coefficient. The Approximation Coefficient and Detail Coefficient result of sub-band 2 followed the same pattern of sub-band 1 Approximation with result within the EER region of 30% to 35%. The sub-band 3 of the Approximation Coefficient and Detail Coefficient has an interesting trend. The best results are from bior1.1 with EER of 16.66 to bior2.8 have an EER of 20.44% with a sharp gradient to a higher EER of 29.70% at bior3.1. The interesting phenomenon is the performance of Approximation of Coefficient from bior4.4 to bior6.8 where the EER is highest (among all the biorthogonal wavelet classification) compared to its performance from bior1.1 to bior2.8. This trend is notice in both diagrams.

3.3. Result on Fusion of Sub-band Feature

The application of fusion in biometric authentication enhances the performance therefore the fusion of the sub-band is initiated to study its performance. The fusion is carried out by first extracting the features before fusing the three sub-band features for classification. The classification result in EER is shown in Figure 13. The Approximation Coefficient has shown better performance in all the classified results except on the bior3.3 with an EER of 26.7%. Table 3 shows the best four performing biorthogonal wavelets. The best result among them is the Detail Coefficient fusion of the bior1.1 three sub-band features scoring an EER of 13.80%. This is followed by the Approximation Coefficient fusion of the bior1.1 scoring EER of 14%. A further experiment is conducted using the best two results as discussed earlier. The features are fused together and classified separately using thirty subjects.

Table 3. Showing the Approx. of Coefficients and Detail Coefficients

Approx. of Coefficients and Detail Coefficients (%)		
Feature Data	**Bior1.1 (%)**	**Bior1.3 (%)**
Approx. of Coefficient Sub-band 3	16.66	16.56
Detail Coefficient Sub-band 3	16.41	16.56
Approx. of Coefficient Fusion	14.00	14.83
Detail Coefficient Fusion	13.80	14.89

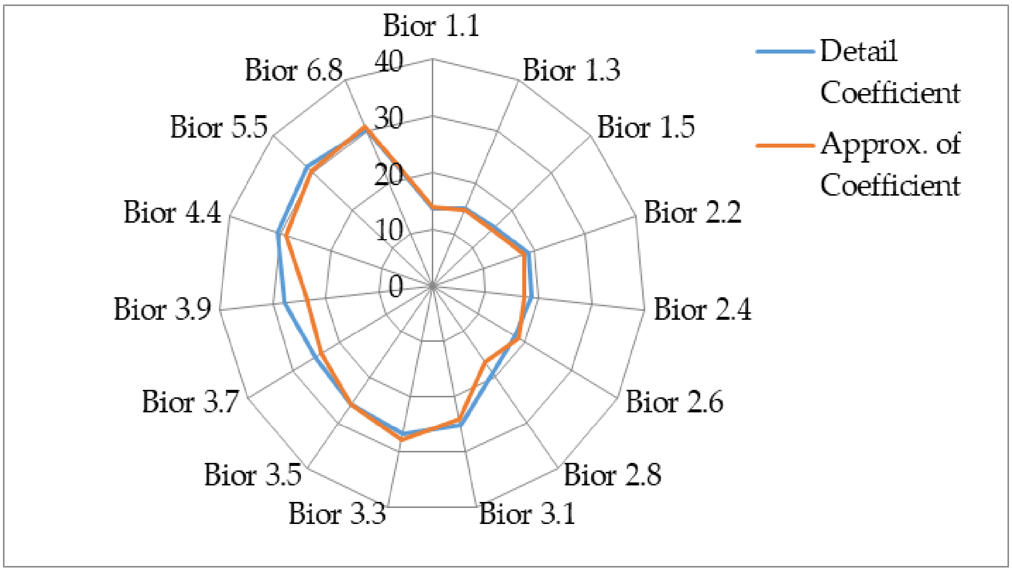

Figure 13. Comparison of the performance of detail and approximation coefficients with different biorthogonal wavelet.

In the experiment, ten features are extracted from the detail coefficient and approximation of coefficient sub-bands of 1, 2 and 3 of the bior1.1 using the best network size. The results of the classification are shown in Table 4.

Table 4. showing the performance of the fusion result

Sub.	Approx. (%)	Detail (%)	Sub.	Approx. (%)	Detail (%)
1	0.00	0.00	**16**	22.84	20.76
2	19.04	17.46	**17**	13.22	15.73
3	12.07	9.70	**18**	14.66	10.13
4	19.83	20.04	**19**	7.11	4.74
5	18.89	13.00	**20**	16.38	9.55
6	4.60	4.17	**21**	13.58	11.35
7	13.36	14.08	**22**	10.20	12.72
8	24.21	19.11	**23**	2.08	2.08
9	14.80	14.08	**24**	19.97	9.27
10	18.10	17.03	**25**	10.13	9.48
11	10.06	4.45	**26**	0.00	0.00
12	15.52	22.49	**27**	8.91	8.76
13	12.72	13.99	**28**	27.23	28.81
14	22.56	24.71	**29**	15.54	14.83
15	20.55	17.10	**30**	3.46	3.05
	Fusion Result			**13.17**	**12.42**

The combination of the sub-bands is based on the result of preliminary the results on the fusion of sub-bands. Finding from the fusion to discriminate between subjects manifested a positive result. It is interesting to note that the preliminary the results on the fusion of sub-bands using twelve subjects and the final experiment using 30 subjects indicated the same trend in term of the difference between the two best results. The initial experimental result had Detail Coefficient surpassing Approximation Coefficient with 0.2% EER while the final experiment has the Detail Coefficient scoring the best too but with a wider margin of 0.75%. More interesting is the fact that most subject's performance is directly related to the two results for example subject 1 and 26 have the same results (0%) on both results. The same is for subject 23 scoring 2.08% EER. They difference between the two classification results on individual assessment shows subject 4, 6, 7, 9, 25, 27, 29 and 30 are close in term of their EER as illustrated in Figure 14. The evaluation has shown the most useful biorthogonal wavelet to apply on a bioelectrical signal with same frequency range as the heart rate.

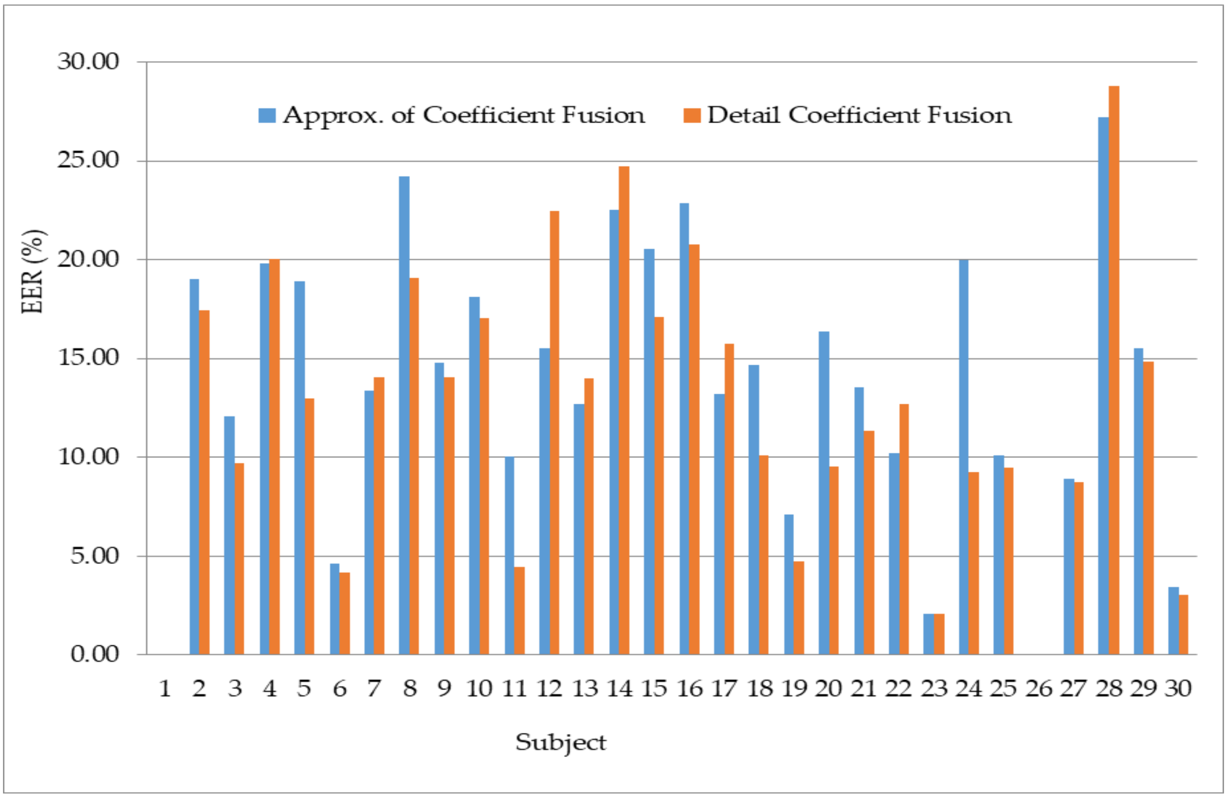

Figure 14. The result from the best network size of fusion of approximation of coefficient and detail coefficient sub-bands in EER

3.4. Result Discussion

As earlier stated, the bioelectrical signal frequency determines the sub-band level to use. It is also necessary to note that different signals will ideally use different biorthogonal (bior) family for feature extraction if using biorthogonal wavelet. To effectively discuss the results, the biorthogonal wavelet is divided into two regions based on the results performance. The first region is from bior1.1 to 2.8 and the second from bior3.2 to bior6.8. The first region (bior1.1 to bior2.8) approximation of coefficient and detail coefficient shows that the sub-band 3 performed better than the sub-band 1 and 2 as illustrated in Figure 5 and 6. The approximation of coefficient sub-band 1(A1) has a stable result in the region. This implies that irrespective of the biorthogonal wavelet family used within the two regions, the result is expected to be slightly different from each other except on bior4.4 where the result had a better result scoring below EER of 30%. Therefore, it will be most suitable to use bior4.4 as shown in the result. In general, sub-band (decomposition level) 1 of approximation of coefficient and detail coefficient of biorthogonal wavelet is suitable for bioelectrical feature extraction with the same frequency range of heart rate. To limit it to a region it will be most suitable to use sub-band 1 of bior1.1 to bior2.8 (first region) of approximation of coefficient and detail coefficient for feature extraction. The fusion of the sub-band improves the result of classification. Therefore, where it is necessary to apply fusion of the sub-bands considering the processing capacity of smart phone, the fusion of either bior1.1 or bior1.3 will be most desirable. The result in Table 3 shows sub-band 3 of detail coefficient using bior1.3 have the best result of EER of 16.41% and for the fusion of features, the best result is the fusion of detail coefficient scoring EER of 13.80%. The result from the thirty subjects have shown consistency with the earlier experiment showing the fusion of the detail coefficient of bior1.1 is effective in the classification of bioelectrical signals.

4. Use Case

Privacy and digital health data are concerned to the health sector therefore, presenting a framework to increase the security of the health data for m-health monitoring is useful. There are wearable devices used for monitoring patients, these devices include smartwatches which should meet some requirements. These requirements include availability of the require data any time, data privacy and security, usability of the data, accuracy of the data. The process describe in this work provides a process for using the most suitable portion of a signal for authenticating a subject taking into consideration the memory requirement to process the data in a mobile device. The used case architecture as shown in Figure 15, will extract data from the patient using the smartwatch then transmit to either the Smart mobile device or computer.

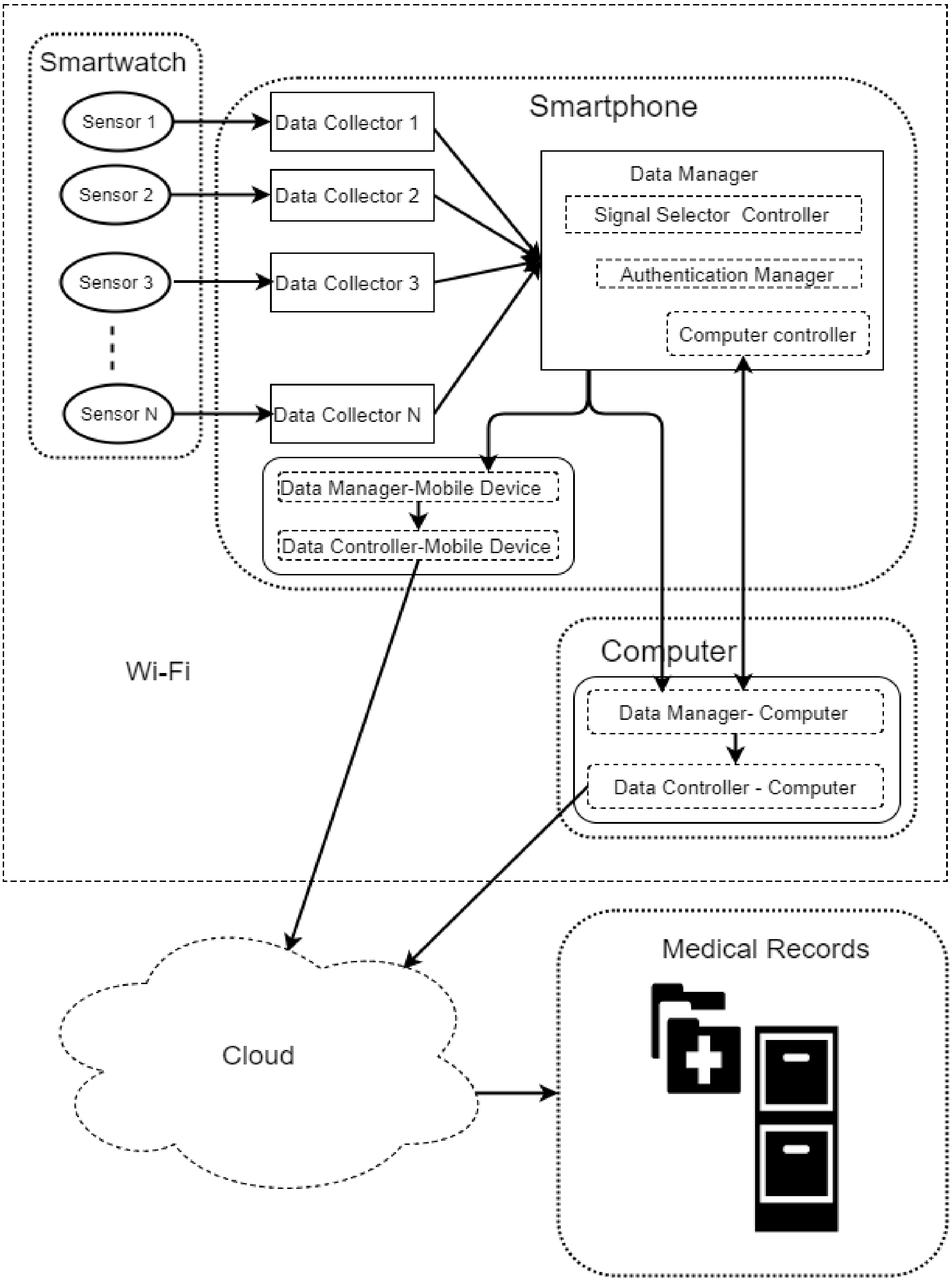

Figure 15. Proposed m-health monitoring and patient authentication framework

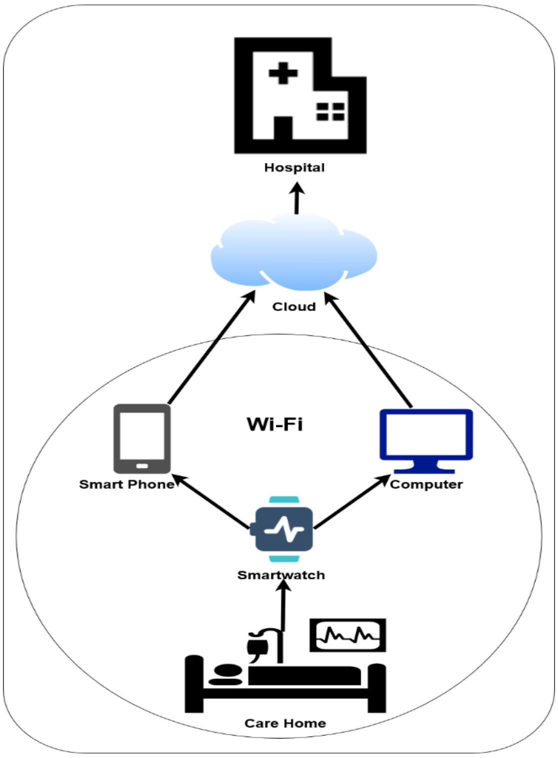

Figure 16. Use Case Architecture

Figure 16 shows a framework of the propose used case system. The framework comprises different components which includes the following:

- The Smartwatch

The smart watch provides the technology to keep track of physical activity using sensors for tracking health information like heart rate, blood pressure other activities useful for m-health monitoring [29]. The smartwatch is the primary data extractor for processing on the either the phone or computer in the framework.

- The Smartphone

Smartphone capability is in the increase, this include its application for variety of activities include data collection and processing [30]. The mobile device in the architecture include the data collection, data management for transmission to the cloud and patient authentication. It also includes a manager for transferring data to the computer.

- The Computing System

The computing system provide a plate form for processing the data as a compliment to the mobile device. The mobile device communicates with the computer for processing and transition of the data to the cloud.

- The Cloud

The cloud provides a channel for transferring the data from the computer or smartphone to the medical data record Centre.

- The Medical records

The medical record Centre provides a plate form for the implementation of the final verification of the data and the patient authentication using the bioelectrical signal transmitted.

5. Conclusion and Future Works

The evaluation has shown the most useful biorthogonal wavelet to apply on a bioelectrical signal with same frequency range as the heart rate. The fusion of decomposed biorthogonal signal of the 3 sub-band levels for classifying bioelectrical signals increases the available information for discrimination. The properties of the signals should be considered when choosing the most appropriate feature extraction technique. The evaluation can be useful for future work applying biorthogonal wavelet for feature extraction of signals, but the drawback is the method is that it is time consuming and takes lot of resources to complete the process. Future work should apply other sub-band fusion of the biorthogonal wavelet family following the procedure. Also, the signals properties can also depend on the activities engaged by the subject therefore, the signal should be segmented and grouped with signal with similar properties. Therefore, future work using this process should segment the signals grouping similar signal segment with the same property based on the activity engaged by the subject while the signal is extracted to improve the result output.

In future works, the proposed framework will be enhanced for implementing m-health monitoring system. The framework and the components will also be evaluated applying different bioelectrical signal extracted from smartwatch.

References

1. Moawd, S. A. & Ali, S. E. 2015. Effect of Over-Usage of Smart Phone in a Non-Neutral Neck Position on Respiratory Function in Female Adults. Int. J. Ther. Rehabil. Res., 4, 104-110.
2. Rao, K. G., Rodda, V. & Rao, B. B. 2017. Qualitative Analysis of Recognition-Based Graphical Password Authentication Schemes for Accessing the Cloud. Indonesian Journal of Electrical Engineering and Computer Science, 7, 507-513.
3. Saevanee, H., Clarke, N. & Furnell, S. SMS Linguistic Profiling Authentication on Mobile Device. Network and System Security (NSS), 2011 5th International Conference on, 2011. IEEE, 224-228.
4. Enamamu, T. S., Clarke, N., Haskell-Dowland, P. & Li, F. 2017. Smart Watch Based Body Temperature Authentication. 2017 International Conference on Computing Networking and Informatics (ICCNI), 1-7. 10.1109/Iccni.2017.8123790. doi: 10.23919/Icitst.2017.8356401
5. Peng, Z. & Chu, F. 2004. Application of the Wavelet Transform In Machine Condition Monitoring and Fault Diagnostics: A Review with Bibliography. Mechanical Systems and Signal Processing, 18, 199-221.
6. Enamamu, T. S., Clarke, N., Haskell-Dowland, P., & Li, F. (2017, October). Smart watch based body-temperature authentication. In *2017 International Conference on Computing Networking and Informatics (ICCNI)* (pp. 1-7). IEEE.
7. https://www.who.int/goe/publications/goe_mhealth_web.pdf (December 2019)
8. Almotiri, S. H., Khan, M. A., & Alghamdi, M. A. (2016, August). Mobile health (m-health) system in the context of IoT. In *2016 IEEE 4th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW)* (pp. 39-42). IEEE.
9. Mallat, S. G. 1989. A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. IEEETransactions on Pattern Analysis and Machine Intelligence, 11, 674-693.
10. Addison, P. S., Walker, J. & Guido, R. C. 2009. Time-Frequency Analysis of Biosignals. Ieee Engineering in Medicine and Biology Magazine, 28, 14-29.
11. Subasi, A. & Ercelebi, E. 2005. Classification of EEG Signals Using Neural Network and Logistic Regression. Computer Methods and Programs in Biomedicine, 78, 87-99.
12. Subasi, A. 2007. EEG Signal Classification using Wavelet Feature Extraction and a Mixture of Expert Model. Expert Systems with Applications, 32, 1084-1093.
13. Jahankhani, P., Kodogiannis, V. & Revett, K. EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks. Modern Computing, 2006. JVA'06. IEEE John Vincent Atanasoff 2006 International Symposium on, 2006. IEEE, 120-124.

14. Gokhale, M. & Khanduja, D. K. 2010. Time Domain Signal Analysis Using Wavelet Packet Decomposition Approach. International Journal of Communications, Network and System Sciences, 3, 321.
15. Prabhakar, S., Mohanty, A. & Sekhar, A. 2002. Application Of Discrete Wavelet Transform For Detection Of Ball Bearing Race Faults. Tribology International, 35, 793-800.
16. Ovanesova, A. & Suarez, L. 2004. Applications Of Wavelet Transforms To Damage Detection In Frame Structures. Engineering Structures, 26, 39-49.
17. Tsou, C., Hsieh, C.-H., Liang, M.-C., Huang, P.-W. & Lee, S.-Y. ECG Acquisition System with Heart Rate Detection and Energy Harvesting For Drivers. Bioelectronics and Bioinformatics (ISBB), 2015 International Symposium On, 2015. IEEE, 31-34.
18. Laine, A. & Fan, J. 1993. Texture Classification by Wavelet Packet Signatures. IEEE Transactions on Pattern Analysis and Machine Intelligence, 15, 1186-1191.
19. Abhyankar, A. & Schuckers, S. 2010. Novel Biorthogonal Wavelet Based Iris Recognition for Robust Biometric System. International Journal of Computer Theory and Engineering, 2, 233.
20. Hariprasath, S. & Venkatasubramaniam, S. Iris Pattern Recognition Using Biorthogonal Wavelet Packet Analysis. Communication Control and Computing Technologies (ICCCCT), 2010 IEEE International Conference On, 2010. IEEE, 830-834.
21. Szewczyk, R., Grabowski, K., Napieralska, M., Sankowski, W., Zubert, M. & Napieralski, A. 2012. A Reliable Iris Recognition Algorithm Based On Reverse Biorthogonal Wavelet Transform. Pattern Recognition Letters, 33, 1019-1026.
22. Prashar, D. & Kaur, M. 2014. Human Eye Iris Recognition Using Discrete 2d Reverse Biorthogonal Wavelet 6.8. International Journal of Scientific & Technology Research, 3, 266-270.
23. Isnanto, R. R. Iris Recognition Analysis Using Biorthogonal Wavelets Tranform For Feature Extraction. Information Technology, Computer and Electrical Engineering (ICITACEE), 2014 1st International Conference On, 2014. IEEE, 183-187.
24. Kapogiannopoulos, G. S. & Papadakis, M. Character Recognition Using A Biorthogonal Discrete Wavelet Transform. 1996.
25. Terwiesch, P. & Mercorelli, P. A Local Feature Extraction Using Biorthogonal Bases For Classification Of Embedded Classes Of Signals. 2000.
26. Hema, C. R., Paulraj, M. & Kaur, H. Brain Signatures: A Modality for Biometric Authentication. Electronic Design, 2008. ICED 2008. International Conference On, 2008. IEEE, 1-4.
27. Kousarrizi, M. N., Teshnehlab, M., Aliyari, M. & Gharaviri, A. Feature Extraction And Classification Of EEG Signals Using Wavelet Transform, SVM And Artificial Neural Networks For Brain Computer Interfaces. Bioinformatics, Systems Biology and Intelligent Computing, 2009. IJCBS'09. International Joint Conference on, 2009. IEEE, 352-355.
28. Tawfik, M. M. & Kamal, H. S. T. 2011. Human Identification Using QT Signal and QRS Complex of The ECG. Online J. Electron. Elect. Eng, 3, 383-387.Reaz, M.B.I., Hussain, M.S. and Mohd-Yasin, F., 2006. Techniques of EMG Signal Analysis: Detection, Processing, Classification and Applications. Biological Procedures Online, 8(1), P.11.
29. Reaz, M.B.I., Hussain, M.S. and Mohd-Yasin, F., 2006. Techniques of EMG Signal Analysis: Detection, Processing, Classification and Applications. Biological Procedures Online, 8(1), P.11.
30. Jahankhani, P., Kodogiannis, V. & Revett, K. EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks. Modern Computing, 2006. JVA'06. IEEE John Vincent Atanasoff 2006 International Symposium On, 2006. IEEE, 120-124.
31. Enamamu, T. S. (2019). *Bioelectrical User Authentication* (Doctoral dissertation, University of Plymouth).