Cardiac Arrhythmias Classification and Compression using a Hybrid Technique

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1 RESEARCH PROBLEM

The electrocardiogram (ECG) is a very important biomedical signal to assess the cardiac health. The ECG waveform is a unique signal that can be broken down into three waves; P, QRS-complex and T, and three segments PR, ST and RR interval as shown in Figure 1 (Rangayyan, 2006). Each segment or wave represents a vital process in the heart. Any abnormalities or irregular rhythmic activities are called arrhythmias. Cardiac arrhythmias are indication of a cardiac disease or heart abnormalities. According to the World Health Organization statistics, cardiovascular diseases (CVD) and ischemic heart diseases are the most leading causes of mortality around the world (WHO, 2011). Heart diseases are not just the leading cause of death nowadays but they are also considered as a modern epidemic. Arrhythmias are usually investigated visually, which is a very hard and time consuming procedure in case of dealing with many patients. Thus, automatic diagnostic methods were developed to provide fast diagnosis that may lead to early detection of heart diseases. Early detection of the heart diseases can prevent the progression of chronic diseases by proper and immediate treatment.

Generally, there is no fixed algorithm to assess the ECG signal. There are plenty of ECG classification methods that produce very sufficient discrimination results. However, when it comes to real-time analysis using low-power devices, the power consumption, complexity of the algorithm and memory required should be taken into consideration.

Wearable health monitoring devices are one of the new interesting fields of reasearch. A miniature ECG sensor can record, compress and transmit the data via cellular transform method to a remote base station or hospital where the data are analysed and stored. The technology of attaching a group of low-power, miniaturised, invasive/ non-invasive light-weight wireless sensors on human body to measure

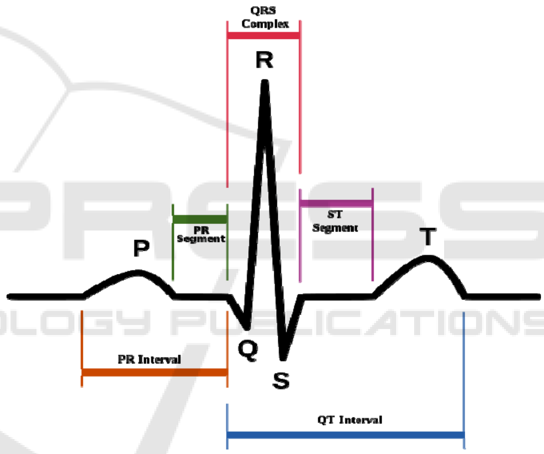

Figure 1: Schematic diagram of normal sinus rhythm for a human heart as seen on ECG (Automated ECG Interpretation, 2014).

the biomedical signals is called Wireless Body Area Network (WBAN) or Wireless Body Area Sensor Network (WBASN). Despite the huge number of published results, WBAN-based healthcare monitoring is still in its infancy. Therefore, there are challenges that have to be addressed while designing such systems. Researchers have to compromise between high reliability and low power consumption and this can be achieved in software level by designing an algorithm with low computational complexity.

The limited band-width channel and battery consumption should be taken into account while real-time transmission. Continuous real-time transmission can consume a lot of energy. Thus, the ECG signal has to be compressed to reduce the data-rate and power consumption. The compression of ECG signal has to be conducted without distorting the clinical features used for diagnosis. In fact the ECG signal has to be processed before compression and transmission.

The purpose of this work is to design a new hybrid technique based on Wavelet Transform (WT). The hybrid algorithm is aiming to combine pre-processing and post-processing tasks which are de-noising, compression and classification of the ECG signals. The ultimate goal of this hybrid algorithm is to obtain sufficient diagnosis results with low computational loads to overcome the limitation of low-powered wearable health monitoring devices. The algorithm will be tested and validated using standard databases and standard evaluate matrices.

The motivations behind this research work are summarized as follows:

- The development of wireless sensor networks for health care requires more sufficient real-time analysis methods that satisfy the limitation of these systems;
- The discrimination of cardiac arrhythmias is still an open research field and many classification techniques have not been tested on ECG signals yet;
- The hybrid compression and classification techniques showed promising performance compared to the classical techniques.

2 OUTLINE OF OBJECTIVES

The objective of this research is to design a hybrid denoising, compression and classification algorithm for ECG signal. This algorithm should be suitable for low-powered wearable ECG devices integrated with wireless technology. This system will consist of the following specific parts and tasks:

- Pre-processing: denoising and preparing signal for compression and classification.
- Compression: encoding scheme to compress the signal before transmission and then decode the signal.
- Post-processing: feature extraction for classification and diagnosis.
- Classification of Arrhythmias: automatic classification of cardiac arrhythmias using a hybrid technique.

3 STATE OF THE ART

3.1 Background and Related Work

According to American Heart Association (AHA), an ECG signal recording must consist of at least 3 individual leads, each with 10 bits resolution and 500 Hz sampling time. If these signals were digitally recorded on an ECG Holter for 24 hours, a huge memory is required to store them. Thus, ECG compression is a must in storage and transmission over a limited bandwidth. In wearable battery-powered devices the sampling frequency can be reduced to 250Hz since the ECG data are used for monitoring and not for deep diagnosis. Since the wearable medical sensor are preferred to be with low-cost and low-power consumption, a proper transmission protocol needs to be followed. Many optimised and new protocols were developed in MAC layer (Otal et al., 2009; Lamprinos et al., 2004), physical layer and application layer (Zhou et al., 2008; Adibi, 2012; Lu et al., 2013). One another solution to reduce the data rate is by compressing the transmitted data to fit into the channel limited capacity. Here we are going to focus on the proper compression methods for ECG signals.

For typical biomedical signals using lossless compression techniques can only achieve Compression Ratios (CR) in the order of 2 to 1. On the other hand, lossy techniques may produce CR in the order of 10 to 1 or more. In lossy methods; there is some kind of quantization of the input data which leads to higher CR results at the expense of reversibility. But this may be acceptable as long as no clinically significant degradation is introduced to the encoded signal. The CR levels of 2 to 1 are too low for most practical applications. Therefore, lossy coding methods which introduce small reconstruction errors are preferred in practice. In other words, the exact reconstruction of the ECG signal is not required, only the important features are important. Thus, the main important factors in compression are: (1) the ability of reconstructing the original signal or the important features from the compressed data, (2) the compression ratio, (3) execution time, and (4) the amount of error between the original and reconstructed signal.

There are many lossless compression techniques such as; null suppression, run-length coding, diatomic coding, pattern substitution, differencing, facsimile, statistical-Huffman and LZ family. On the other hand, the lossy compression methods are; polynomial predictors and interpolators, orthogonal transforms, Fan, AZTEC, CORTES, TP, DPCM, ADPCM, broad family of sub-band and wavelet coding, probabilistic neural networks and adaptive Fourier coefficient techniques. There are also recent trials to combine the lossy and lossless techniques specifically for ECG signal (Abo-Zahhad et al., 2014).

There are many measures for assessing techniques for the adequacy of the ECG compressor. The residual of the signal, which is the difference between the original signal and the reconstructed compressed signal, is one of the widely used measures. But the low residual doesn't guarantee that the reconstructed signal has acceptable quality for clinical diagnosis. The reconstruction error is defined as Percent Root Mean Square Difference (PRD) and it defined as follows:

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=0}^{N-2}\left[x(n) - x_{rec}(n)\right]^2}{\sum_{n=0}^{N-2}\left[x(n)\right]^2}} \times 100\% \tag{1}$$

where N is the total number of samples in the ECG signal x(n), and x_{rec}(n) is the reconstructed ECG signal.

A new compression measure called "quality score" (QS) was suggested by Fira and Goras (2008) to represent the ratio between the compression ratio (CR) and the PRD as shown in (2). The high quality score indicates a good compression performance.

$$QS = CR/PRD \tag{2}$$

Biomedical signals can be compressed in time domain, frequency domain, or time-frequency domain (Cetin et al., 2000). Wavelet Transforms (WT) are one of the recent transform method that could produce higher coding results than time-domain coding methods. The new hybrid compression techniques combine the compression and the classification techniques to overcome the constraints of mobile ECG Holters (bandwidth, area, power and resolution). Alvarado et al., (2012) introduced a time-based compression technique integrated with a classifier. This method can perform diagnostic analysis (classification) method directly on the encoded signal without reconstructing it. This is done by sampling the signal using finite rate of innovation (FRI) method and performing compressive sensing (CS) on it. This method allows real-time analysis, compression, classification and transmission of the ECG signal. The classification is done in the pulse domain resulted from FRI sampler which is in fact a compression technique.

Ahmed et al. (2007) introduced a new hybrid compression technique for ECG signals using the singular value decomposition (SVD) combined with discrete wavelet transform (DWT). The central idea is to transform the ECG signal to a rectangular matrix, compute the SVD, and then discard small singular values of the matrix. The resulting compressed matrix is wavelet transformed, thresholded and coded to increase the compression ratio. The technique has been tested on ECG signals obtained from MIT-BIH arrhythmia database. The results showed that data reduction with high signal fidelity can thus be achieved with average data compression ratio of 25.2:1 and average PRD of 3.14%. Comparison between the obtained results and recently published results showed that the proposed technique gives better performance.

Some works did combine the denoising scheme with the compression scheme using wavelet transform and other hybrid techniques. Sayadi et al. (2008) represented an efficient denoising and lossy compression schemes for ECG signals based on a modified extended Kalman filter (EKF) structure. The signal is reconstructed with regard to the dynamical equations of the model. The performances of the proposed method are evaluated using standard denoising and compression efficiency measures. Several MIT-BIH ECG databases were used for performance evaluation and results shown that both applications can contribute to enhance the clinical ECG data denoising and compression performance. For denoising, an average SNR improvement of 10.16 dB was achieved, which is 1.8 dB more than the next benchmark methods such as MAB-WT or EKF2. Results showed a typical average CR of 11.37:1. Consequently, the proposed framework is suitable for a hybrid system that integrates these algorithmic approaches for clean ECG data storage or transmission scenarios with high output SNRs, high CRs, and low distortions.

We can summarize that compression techniques can use hybrid techniques to achieve the proper CR, resolution and execution time. Also, compression can integrate hybrid functions like denoising, feature extraction and classification of arrhythmias.

Most of the approaches that have been developed for classifying cardiac arrhythmias based on surface ECG (non-invasive).The classification methods can be off-line methods or on-line (real-time) methods. The offline technique may not be preferable in case of emergency cases due the delay in data analysis. A lot of work has been done based on Artificial Neural Networks (ANN) techniques in classifying the ECG signals. In fact, the ANN is a very powerful non-linear mathematical tool based on training of multilayer neural networks which are sometimes called Multi-Layered Perceptron (MLP) and it is mainly used in the pattern recognition research area (Duda et al., 2001). ANN showed superior results in discriminating the ECG signal (Bortolan et al., 1993; Silipo et al., 1998; Tsipouras et al., 2005). ANN could combine the pre-processing and post-processing techniques for arrhythmia classification, ischemia detection, and recognition of chronic myocardial diseases (Silipo et al., 1998). Silipo et al., (1998) also discussed the issue of reducing the size of the network to get the same results or better.

Although, the ANN is a typical classifier used in the hospital based ECG monitoring devices, a huge ANN requires a lot of training time and computational power which make it not a preferable option for mobile ECG analysers for home-monitoring.

Wavelet Transform (WT) is mainly used for extracting features from signals. There are many powerful wavelet transformation techniques such as, Continues Wavelet Transform (CWT), Discrete Wavelet Transform (DWT). For example, Übeyli used DWT in analysis of ECG changes in partial epileptic patient (Übeyli, 2008). The choice of the wavelet family as well as the selection of the analysing function into these families should be proper and based on some criteria. According to Senhadji et al., (1995) the criterion used in the first case is the correct classification rate, and in the second case, the correlation coefficient between the original pattern and the reconstructed one. Senhadji's system was capable of discriminating between normal, premature ventricular contraction, and ischemic beats. Wavelet transform analysis has high detection performance but has huge computation overhead which also consumes a lot of power. Bulusu (2011) also used DWT to extract features but utilized Support Vector Machine Approach (SVM) for arrhythmia classification. The SVM is a binary classifier method which aims to find the optimal separating plane and the data points that determine the position and the orientation of the plane. Those planes are called the support vectors. Bulusu extracted two types of the features; morphological features and DWT features. The design used 12 morphological features (QS Width, Pre RR Interval, Post RR Interval, QR Width, RS Width, Mean Power Spectral Density, Area Under QR, Area Under RS, Autocorrelation Value, ST segment Deviation, Slope of ST, Correlation coefficient with class template) and 191 discrete wavelet transform coefficients (DWT). The features extracted are used to train the SVM to classify six different heart arrhythmias (N: Normal, V: Premature Ventricular Contraction, A: Premature Atrial Contraction, R: Right Bundle Branch Block, L: Left Bundle Branch Block, F: Fusion). This system resulted in an accuracy of 93.33% for ST-episode detection and a heartbeat classification accuracy of 90.66%. It also achieved a 96.35% accuracy compared with the commercially available Monebo software, which classified heart beats into only two classes with an 89.18% accuracy. The drawback of this system is that it takes a lot of time during the learning phase. Bulusu recommended the use of Hierarchical Binary Decision Tree in the future to reduce the number of classifiers needed during classification and to overcome the low speed while training.

Syntactic analysis method has been utilized in automatic diagnosis. This method depends on the idea of transforming the original signal into vectors of strings. The transformed signal is then syntactically analysed to determine if the transformed signal characterizes any fault in the system under analysis. Many syntactic methods have been proposed for automatic diagnosis (Koski et al., 1995; Trahanias et al., 1990). For example, the regular state machines, complex state machines and fuzzy state machines have been utilized to perform syntax analysis that can deal with imperfect and imprecise input signals. Tumer et al. (2003) use two level automatons (smart detection tools) with the syntactic analysis method. The main automatons used to identify the overall signal and the sub-automatons to identify particular segment in the signal (i.e. QRS and T-wave). Also, the system incorporates fuzziness future to add flexibility to the system in order to identify abnormalities and noises. The syntactic analysis method showed good results in diagnosis of nonlinear systems (ECG), but it is noise-sensitive and has huge computations.

The new classification algorithms integrate more than one method to have more accurate results with less power consumption and no huge computations. These new techniques are called hybrid techniques and the main objective behind them is to utilize them for miniature mobile health-care devices. Zhou et al., (2009) combined the time-domain to detect the QRS with syntactic method to classify the rhythm. The rhythm classifier was designed to recognize two kinds of QRS complex rhythms: sinus and ventricular. The classifier is simple, fast and can be implemented into a microprocessor or a DSP chip. It was implemented into STAR (Système Télé-Assistance Réparti) which is a real-time remote continuous cardiac arrhythmia detecting and monitoring system and it showed effective results.

Kamousi (2011) introduced a new morphology-based algorithm by employing Dynamic Time Warping (DTW) to measure the overall similarity in patterns of different rhythms and distinguished VT (ventricular tachycardia) from other rhythms such as SVT (supraventricular tachycardia) based on morphology differences. DTW is originally used in automatic speech recognition by measuring the overall similarity in patterns regardless of their differences in time or speed. It minimizes the difference between two given sequences by nonlinearly warping them in the time dimension. This method was utilized to improve the classification rate of current ICD device. Typical Euclidean distance method (measures distance between two signals) can't capture the similarities of two similar shapes with equal point to point distance. On the other hand, DTW aligns the time axis and calculates a more efficient distance measure between them and gives better classification results.

Peng (2011) investigated in his work a low cost, automatic real-time architecture for ECG arrhythmia classification. The work integrates the Euclidean Distance calculator and PCA methods for classifying the different cardiac rhythms. The main contribution in Peng's work is the hardware implementation on FPGA platform. The on-chip cache memory of the system was used to store the rhythms used in classification. As a result, the memory was optimized and power consumption was reduced.

Since the ECG data may differ from patient to patient, or differ for the same patient during the day, the traditional trained classifiers may fail if applied to the same patient. One of the approaches proposed by Hu et al., (1997) to overcome this issue is to have two classifiers. A global classifier that relies on a database or table of known heart rhythms and a local classifier that trains on patient's specific ECG recordings.

As most of the classification methods depend significantly on the feature extraction step, the selection of the best feature extraction method will depend on the major value considered for training time, training and testing performance (Khorrami et al., 2010).

3.2 Motivations

There are many algorithms that are trying to minimize the computational complexity and increase the reliability of the analysis results. However, few proposed algorithms integrate pre-processing, compression and classification in a hybrid manner and with minimal computational tasks. Therefore, we propose a new hybrid techniques method of compression and classification of cardiac arrhythmias. This method will combine denoising, compression and features extraction by utilizing wavelet transform since it showed promising results in ECG signal analysis. Thus, this work is aiming to tackle the challenges of real-time compression and classification of ECG data using battery-powered wearable health monitoring devices. The ultimate goal of this work is to find a novel and more reliable algorithm to analyse the remotely monitored ECG by means of less computational complexity requiring minimal number of processing and computational stages.

4 METHODOLOGY

The rhythm of the heart is indicated by beats per minute (bpm). The normal heart rate is about 70 bpm but lower than 60 bpm during activity is abnormal. The instantaneous heart rate could reach values as high as 200 bpm during hard exercise or athletic activity; but higher than this could be due to illness, disease, or cardiac abnormalities (Rangayyan, 2006). Thus, the proper measurements of ECG should be taken to avoid contrary results. In this study standard ECG data will be considered for analysis and other real data will be collected to double check the performance of the algorithms proposed.

The ECG signal can be analysed directly using time-domain analysis methods or transform-domain methods (Manikandan et al., 2014). Unlike the direct compression or analysis methods, the transform-methods transform the signal into a frequency-domain signal which reveals other features like the frequency and energy distribution of the signal.

Wavelet transform (WT) methods will be considered in this study due to their powerfulness in decomposing the different ECG waveforms. The wavelet-based techniques fit with the standard signal filtering methods and encoding schemes and thus producing good compression results (Addison, 2002). The ECG signal can be decomposed into J decomposition levels as shown in Figure 2, using lowpass *g(n)* and highpass *h(n)* FIR filter banks and then down-sampling by a factor of 2. The decomposed signal in each level is divided into low frequency signal (a_n) and high frequency signal (d_n). The low frequency signal a_n is called the approximation signal and the high frequency signal d_n is called the detail signal. The low frequency signal is decomposed again into two signals and so on up to d_J and a_J. The filter banks are constructed from wavelet basis functions such as Haar,

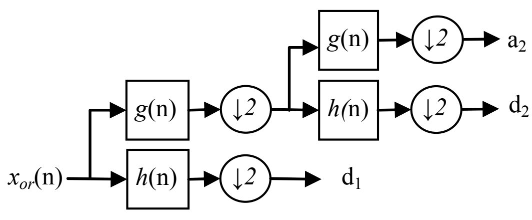

Figure 2: DWT with 2 level of decomposition.

Daubechies, Biorthogonal, Coiflet, Symmlet, Morlet, and Mexican Hat. The selection of wavelet transform function mainly depends on the application. The decomposed signal can be reconstructed back again into the original signal using reconstruction filters, which are the inverse of the decomposition filters.

The relation between the frequency of the signal and the decomposed sub-bands is as follows:

$$a_j = 0 - \frac{F_S}{2^{j+1}} \tag{3}$$

$$d_j = \frac{F_S}{2^{j+1}} - \frac{F_S}{2^j} \tag{4}$$

where, a_j is the approximation coefficient, dj is the detail coefficient, F_s is the sampling frequency and j is the decomposition level. The upper sub-bands hold the high frequency contents and the frequency sub-band is decreasing as the signal is decomposed further.

In our research, the algorithm is aiming to compress and classify the ECG signal using wavelet transform as illustrated in Figure 3 and described in the following sub-sections.

4.1 Data Description

To validate our outcomes and results, standard ECG data will be used from standard databases. The PhysioNet website is a site dedicated to many digitized physiological signals. The MIT-BIH database will be adopted for analysis in this work since it consists of ten databases for various test purposes; i.e., the Arrhythmia Database, the Noise Stress Test Database, the Ventricular Tachyarrhythmia Database from Creighton University Cardiac Center, the ST Change Database, the Malignant Ventricular Arrhythmia Database, the Atrial Fibrillation/Flutter Database, the ECG Compression Test Database, the Supraventricular Arrhythmia Database, the Long-Term Database, and the Normal Sinus Rhythm Database. Initially we used the MIT-BIH arrhythmia (*mita*) database as a starting point for our analysis. The *mita* consists of 48 ECG recordings each with 30 minutes duration. The recordings are sampled with a sampling rate of 360Hz and 11-bits resolution over a ±5mV range.

4.2 Pre-Processing

Like any electric signal, in practice the ECG signal is corrupted by some artifacts like (Rangayyan, 2006):

- Electromyogram (EMG).
- Respiration and electrodes motion artifacts.
- Power line interference (50/60Hz).
- Base-line wandering.
- Motion artifacts.

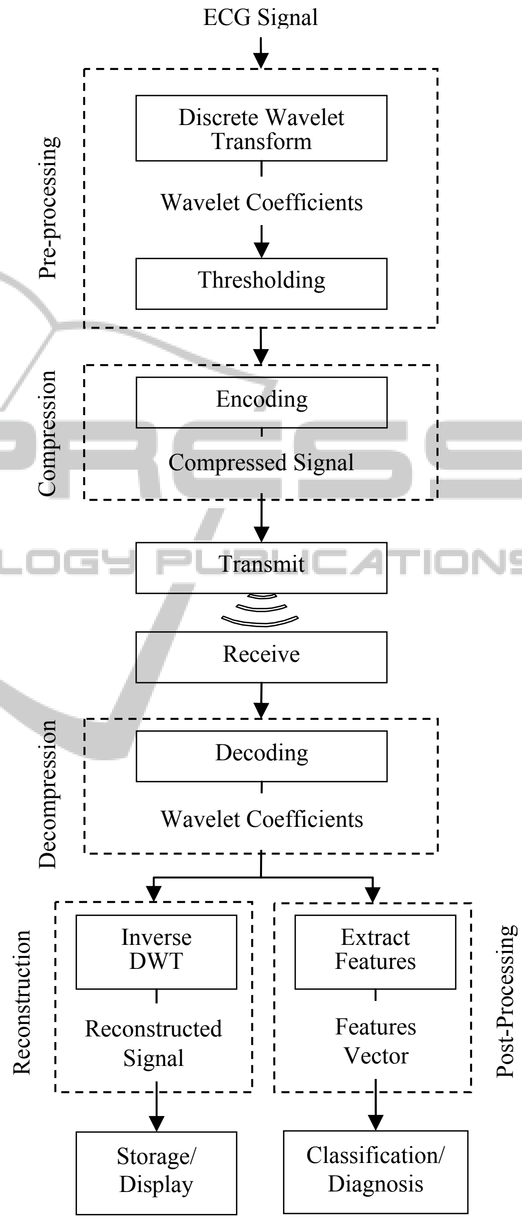

Figure 3: Proposed hybrid classification algorithm.

Those noise signals reduce the quality of the ECG signal and prevent the correct detection and classification of the different rhythms. Thus, the pre-processing of the ECG signal is of great importance, since it contributes significantly to overall compression and classification results.

For example, Figure 4 shows a typical clean ECG signal and the same signal correlated with

50Hz power line noise. The frequency spectrum indicates the low frequencies of the clean signal. On the other hand, the frequency spectrum of the noisy signal shows a 50Hz noise spectrum. To filter these noises, digital filters can be applied on the time-domain signal or thresholds can be applied on the transform-domain signal. Since digital filtering is a widely used procedure, we are going to discuss the de-noising procedure using thresholds.

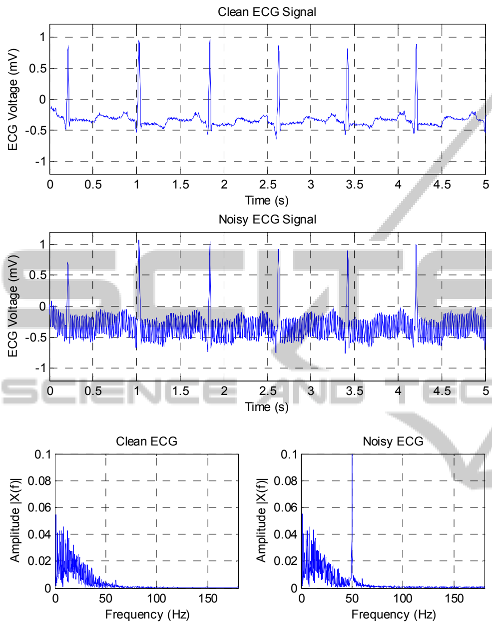

Figure 4: A typical ECG signal (mita record 100) (above), with 50Hz interference (middle), and their frequency spectrums (below).

4.2.1 Threshold

The DWT can decompose the ECG signal into sub-bands of different waveforms. By assessing the decomposed signal in Figure 5, we can see the different waveforms of the ECG signal and the noise signals. The high frequency noise signals are located in the upper sub-bands d_1 and d_2. The power line periodic noise is clear in d_3 sub-band. The advantage of the wavelet decomposed coefficients is that the noise signal can be easily removed using a threshold. The threshold can be fixed for all sub-bands or adaptive as in (5).

$$T_n = \sigma\sqrt{2\log N} \tag{5}$$

where, σ is the standard deviation of the Gaussian noise of each sub-band and N is the number of samples in the same sub-band (Quotb et al., 2011). The Gaussian noise σ is calculated by (6).

$$\sigma = \frac{median(dj[n])}{0.6795} \tag{6}$$

where $d_j[n]$ is the sub-band signal. However, the median operation requires a sorting procedure of the sub-band coefficients. Sorting process may take time and increases the algorithm's overhead, and this is not desired in our design. Replacing the median by the average value of the sub-band coefficients will not give us the desired results. A quickselect algorithm can replace the typical sorting algorithm (Quickselect, 2014). In fact quickselect is a quick sorting algorithm that reduces the averaging complexity from $O(n \log n)$ to $O(n)$. The complexity reduction of other tasks will be investigated during the project.

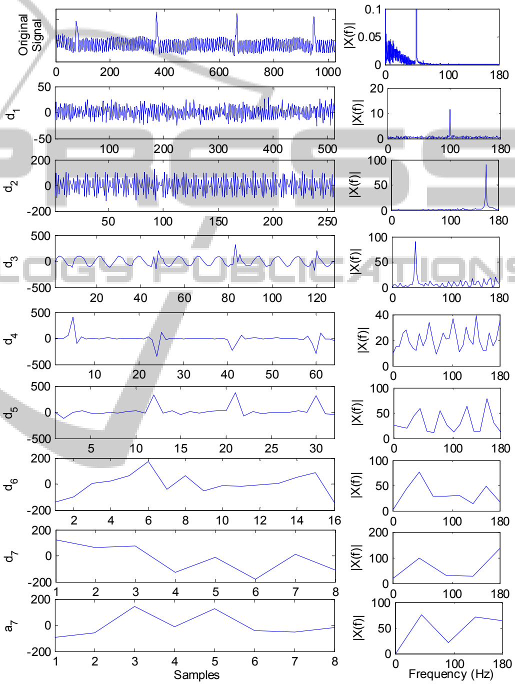

Figure 5: DWT sub-band coefficients of the noisy ECG signal (mita record 100) and the frequency spectrum of each sub-band.

Other fact about thresholds is that they can be soft or hard. In hard thresholding, the values less than the predetermined threshold are set to zero and the values higher than the threshold are kept. On the other hand, in soft thresholding the predetermined threshold is subtracted from the values greater than the threshold, while the values lower than threshold are set to zero. Practically, the soft threshold produces smooth and continuous data which make it suitable for denoising, while the hard threshold is preferable in case of compression.

4.3 Compression/Decompression

The compression of the ECG signal is going to be conducted on transformed-domain signal, since experimenting compression on the transformed signal showed better compression performance than time-domain compression.

Lifting wavelet transforms (LWT), wavelet packet transforms (WPT) and discrete wavelet transforms (DWT) will be utilized individually or in combination in this study to produce the best real-time performance in terms of less complexity and fast real-time performance. Compression is conducted on the sub-band coefficients by encoding them and removing the redundant data. This step depends mainly on the thresholding procedure. The threshold indicates the critical data to be preserved and the non-critical data that can be discarded. The thresholding procedure will significantly affect the compression ratio (CR) and quality of the reconstructed signal. The following subsections will describe the thresholding and encoding procedures proposed to be adopted.

4.3.1 Thresholding

The thresholding procedure for compression can be different than the filtering threshold. Unlike the adaptive threshold, in this work the threshold ($Thres_{Sb}$) in (7) was calculated based on the bit-depth (B_{Sb}) of each sub-band and the desired preserved bit-length (I_{Sb}). The sub-band bit-depth B_{Sb} is the most significant bit of the maximum-magnitude coefficient in the sub-band. While, the preserved-length I_{Sb} is controlled according to the desired compression performance where Sb stands for the sub-band coefficients $d_1, d_2,.., d_J$ and a_J.

$$Thres_{sb} = 2^{B_{sb} - I_{sb} + 1} \tag{7}$$

A round-off mechanism is applied to the DWT coefficients before thresholding and encoding by adding 2^{Bn-Isb} to all coefficients to reduce the truncation error (Chan et al., 2008). Where, B_n is the bit depth before round-off mechanism and B_{Sb} after round-off.

4.3.2 Encoding

Encoding the DWT coefficients showed sufficient results since the upper sub-bands mainly contain noise-like signals which are not vital and can be discarded. Thus, the higher sub-bands can be encoded using fewer bits.

Before encoding the coefficients, the mean of the approximation coefficient a_J is subtracted and it will be added later on at the reconstruction stage. To encode the coefficients, first they are compared to the calculated sub-band threshold $Thres_{Sb}$ in (7). If the magnitude of the coefficient is greater than or equal to the sub-band threshold, it is considered as significant; otherwise it is considered as insignificant. The desired bits of interest of the significant coefficient will be sent to the bits-of-interest (BOI) packet and a one will be sent to the significant map (SM) stream. The SM stream indicates the sequence of significant and insignificant coefficients by ones and zeros, respectively. The BOI are the extracted bits from $B_{sb}+1$ to $B_{sb}-I_{sb}+1$, which represent BOI range, including the sign bit ($B_{Sb}+1$). In this works, each BOI is stored into one byte and the same for BOI range. Thus, I_{Sb} is no more than 6 (i.e. bits 0 to 6 hold the extracted bits and bit 7 for the sign bit).

To reduce the redundant zeros in SM stream and increase the compression ratio, it is divided into bytes and then running length encoding (RLE) is applied on the SM bytes. The RLE is a well-known method that replaces the consecutive bytes with their value followed by their number of copies (e.g. x=1 1 0 0 0 5 0 0 0 9 0 0 0 0 0 3 3 3, will be x_{enc}=1 2 0 3 5 1 0 3 9 1 0 5 3 3). The SM can be easily encoded (SMe) by encoding the consecutive zeroes. One byte is enough to represent the number of consecutive zeros up to 255 zeros. The last two sub-bands (a_J and d_J) have fewer samples and less consecutive zeros and thus RLE method was not applied to them.

In order to decode the encoded coefficients, headers have to be designed properly to indicate the content and the length of each sub-band. However, the headers have to be designed to be as short as possible to avoid increasing the length of the encoded packets. In fact, the headers can be designed with secret keys to encrypt the private data of the patient while transmission over public networks (Miaou et al., 2002).

4.4 Feature Extraction

Based on our initial review, we decided to extract the features from the wavelet coefficients to feed the classifier. Features should be selected carefully to fit the designed classifier. The possible features can be detected are:

- QRS complex: or the R-R interval which is used to calculate the heart rate (HR) and heart rate variability (HRV).
- P-wave and T-wave.
- Power and energy.
- Other parameters: such as minimum, maximum, mean and standard deviation.
- The wavelet coefficients.

QRS is considered as an entry point for classification schemes since HR and HRV are derived from the RR-intervals. Thus, it has to be estimated accurately. So far, Pan-Tompkins detection method (Pan and Tompkins, 1985) was tested to detect the QRS and calculate the HRV of the ECG signal over time. Detection using wavelet transform will be investigated during the PhD period since it showed better results than Pan-Tompkins detection algorithm (Köhler et al., 2002).

4.5 Classification

ECG classification in this project describes the automated ECG interpretation or diagnosis process. In order to classify an ECG signal; first it should be pre-processed and then features are extracted from it. The possible extracted features were discussed in the previous sub-section. The features in this project will be extracted from a single-channel lead.

Artificial neural networks (ANN), cluster analysis, fuzzy logics and many other methods were utilized to classify the ECG arrhythmias. However, most of these methods are complex and require high computational loads. Therefore, the main goal of this research is to find a classifier that gives sufficient diagnosis results with low computational loads by modifying some existing methods or integrating two methods.

4.6 Clinical Approvals

Although there are many publications about ECG arrhythmias classification, just few of them had clinical approvals. Our aim is to get clinical approval for the diagnostic results from cardiologists at Sultan Qaboos University Hospital (SQUH). This step will be done since low reconstruction error doesn't guarantee that the reconstructed signal has acceptable quality for clinical diagnosis.

Cardiologists are expected to interpret the signal with different arrhythmias and judge our automatic analysis results correspond to each arrhythmia. Real ECG data from the hospital will be collected as well for analysis.

5 EXPECTED OUTCOME

We expect the following scientific contributions: (1) a new compression algorithm using wavelet transforms but with less computational overheads; (2) a novel hybrid compression and classification algorithm that can contribute to improve the real-time diagnosis for low-powered wearable devices; and (3) explore new features that can be utilized for classification of specific cardiac diseases.

6 STAGE OF THE RESEARCH

This research is divided into three broad phases. Some phases are done in parallel and final integration requires a remarkable care. Some of these phases are generalisation of the proposed algorithm and there are several unanswered questions regarding the final architecture and performance of the hybrid classification algorithm.

6.1 Phase 1: Pre-Processing and Compression using WT

This phase involves the preparation of raw ECG signals by processing them for compression and classification. The pre-processing will be conducted using WT and the results obtained will be compared to the results led by digital filters. The compression of ECG signal using a modified discrete wavelet transform (DWT), bit-field preserving (BFP) and running-length encoding (RLE) method was conducted and it showed superior results compared to other well-known methods. The parameters of the method may be tuned later on in the integration phase. More investigation on the compression scheme using WT will be conducted.

6.2 Phase 2: Classification and Feature Extraction

In classification, the most important step is obtaining the best features. So far, different features were extracted from the DWT decomposed signal. Those features were studied by plotting them correspond to different arrhythmias. Initially, some distinguished results can be visually spotted. However, a sophisticated classifier has to be utilized for automatic ECG classification. The proper classifier that is going to fulfil the limitation and desired requirements is still under investigation.

6.3 Phase 3: Integration

This task is significantly contributing in the novelty of this work. The main goal is to integrate the compression and classification algorithms with less number of steps to reduce the computational load and complexity. Initial prospective is to apply compression on the decomposed coefficients and then after decompressing those coefficients, features are extracted from them and used for classification.

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