



Assessing Fetal Cardiac Health during Pregnancy from Abdominal ECG Signal

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**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF REQUIREMENT FOR THE DEGREE OF THE
MASTER OF COMPUTER SCIENCES AT YARMOUK UNIVERSITY, IRBID, JORDAN.**

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I

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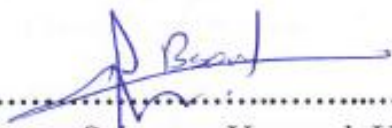
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List of Abbreviations

FECG	Fetus Electrocardiogram
MECG	Maternal Electrocardiogram
FHR	Fetus Heart Rate
SNR	Signal to Noise Ratio
HR	Heart Rate
HRV	Heart Rate Variability
DTCWT	Dual-Tree Complex Wavelet Transform
DWT	Discrete Wavelet Transform
SVM	Support Vector Machine
AVF	Adaptive Volterra Filter
ANC	Adaptive Noise Canceller
LC	Liner Combiner
RLS	Recursive Least Square
LMS	Least Mean Square
NLMS	Normalized Least Mean Square
IFFT	Inverse Fast Fourier Transform
FIR	Finite Impulse Response
FTF	Fast Transversal Filter
BSS	Blind Source Separation
FastICA	Fast Independent Component Analysis
BSSR	Blind Source Separation with Reference
ICA	Independent Component Analysis
MICA	Multidimensional Independent Component Analysis
PCA	Principle Component Analysis
IMF	Intrinsic Mode Function
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
ANN	Artificial Neural Network
FLANN	Function Link Artificial Neural Network

LWT	Lifting Wavelet Transform
ANFIS	Adaptive Neuro Fuzzy Inference System
SWT	Stationary Wavelet Transform
SVD	Singular Value Decomposition
ANS	Autonomic Nervous System
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
Hz	Hertz
bpm	Beat Per Minute
dB	Decibel

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الملخص

مطالعة، براءة فواز. تقييم صحة قلب الجنين أثناء الحمل عن طريق إشارة القلب البطنية. ماجستير في علوم الحاسوب، رسالة، قسم علوم الحاسوب، جامعة اليرموك، ٢٠١٧.
(المشرف: د. عبدالرؤف خالد بصول)

يعد الكشف عن صحة قلب الجنين من اشارة القلب البطنية مهم جداً لتشخيص حالة القلب الصحية وعيوبه الخلقية، وتعد هذه العيوب من الأسباب الرئيسية للوفيات ذات العلاقة بالقلب. تعرض هذه الأطروحة نظاماً جديداً للكشف عن صحة قلب الجنين بالإعتماد على إشارة البطن المسجلة من بطن المرأة الحامل. النظام المقترح يلغي الضجيج من إشارة البطن باستخدام مرشح Bandpass ويصحح الانحراف في الإشارة. يتم استخراج الإشارة الخاصة بقلب الجنين من خلال تطبيق خوارزمية خوارزمية تحليل المكونات المستقلة السريعة. ثم لبناء إشارة معدل تغير نبضات القلب، يتم استخدام خوارزمية Cubic Spline Interpolation. ومن أجل تحليل هذه الإشارة يستخدم خوارزمية Dual-Tree Complex Wavelet Transform لاستخراج بعض الميزات الإحصائية من معاملاتنا. وتصنف هذه الإشارة باستخدام Support Vector Machine ويتم مقارنة نتائج هذا المصنف مع J48 و Naïve Bayes لإيجاد أي من هذه المصنفات أفضل لهذا النظام وكان Support Vector Machine هو الأفضل. تم إختبار النظام المقترح باستخدام ١٠٥ إشارات قلب بطنية، وكانت دقة هذا النظام لكافة الإشارات في التصنيف بنسبة ٩٧.١٤%، ونسبة الإشارات الغير سليمة التي صنفت بشكل صحيح ٩٥.٢٣%، والإشارات السليمة المصنفة بشكل صحيح ٩٨.٤١%.

الكلمات المفتاحية: تحليل الإشارات، تحليل معدل ضربات القلب، استخراج مميزات، الكشف عن صحة قلب الجنين، خوارزمية تحليل المكونات المستقلة السريعة.

Abstract

Matalkeh, Bara'ah Fawwaz. Assessing Fetal Cardiac Health During Pregnancy From Abdominal ECG Signal. Master of Computer Science, Thesis, Department of Computer Sciences, Yarmouk University, 2017. (Supervisor: Dr. Abd Alraouf K. Bsoul).

Monitoring of fetus cardiac activity and health from abdominal Electrocardiogram signal is very important to diagnose fetus cardiac health and defects which are the main reasons for related deaths. This thesis proposed a novel method for fetus cardiac health detection based on abdominal signals recorded from the abdomen of a pregnant woman. The proposed method removes the noise from the abdominal signal using Bandpass filter and correct baseline wander. The fetus Electrocardiogram signal is extracted by applying Fast Independent Component Analysis method. Then in order to construct Heart Rate Variability signal, Cubic Spline Interpolation method is used. Dual-Tree Complex Wavelet Transform is used to decompose the Heart Rate Variability signal and extract statistical features from its coefficients. Support Vector Machine is used to detect any abnormality in the fetus cardiac health and this classifier is compared with J48 and Naïve Bayes classifiers to find which one is suitable for this method. The Proposed method is tested on 105 noninvasive abdominal signals. Accuracy, sensitivity and specificity are used for arithmetical evaluation of this method, which is achieved 97.14% accuracy, 95.23% sensitivity and 98.41% specificity using Support Vector Machine classifier.

Keywords: Signal analysis, Dual-Tree Complex Wavelet Transform, Heart Rate Variability analysis, features extraction, fetal cardiac health detection, FastICA algorithm, Cubic Spline Interpolation method.

Chapter 1

Introduction

1.1 General Overview

Every year, one out of 100 babies in Jordan born with some heart disease (Al-Hakim, 2011). Therefore, monitoring the heart of a fetus during pregnancy is of paramount importance to avoid any irrevocable problems. Congenital heart defects originate when the heart is forming and this defects can affect the function of the heart (Anisha, Kumar and Benisha, 2014).

Fetus Electrocardiogram (FECG) monitoring is a technique that extracts important information about the function of a fetus cardiac during pregnancy. The monitoring is performed invasively or by a noninvasive approach. Invasive methods performed as electrodes placed inside the mother's uterus to the scalp of her fetus. Although the method gives more accurate FECG signal, it constitutes a danger to the mother and her baby. FECG signal can be acquired noninvasively by placing electrodes on the mother's abdomen. Thereby, noninvasive method provides a signal that is contaminated by noise, baseline wander as well as the Maternal ECG (MECG) signal. Sources of noise can be from respiration, power line interference, instrumental noise, muscle contractions and electromyography. FECG signal is extracted by suppressing the MECG signal from the abdominal signal, but before that the noise is removed by using some techniques to improve the extracted signal (Luo, 2012; Țarălungă *et al.*, 2014).

FECG signal contains three waveforms; P-wave, QRS complex and T-wave as shown in Figure 1. These waves are produced by the heart's muscle contraction; the P-wave occurs due to the contraction of the atrial, the QRS complex due to the ventricles contraction, finally the T-wave follows each contraction of the heart. The main characteristics that need to be extracted from the FECG signal are Fetus Heart Rate (FHR), waves amplitude and duration of the waves (M. A. Hasan et al. 2009a). However, such information can be extracted only from direct FECG signal. Noninvasive FECG signal has several types of noise which obscure correct reading of the waveform.

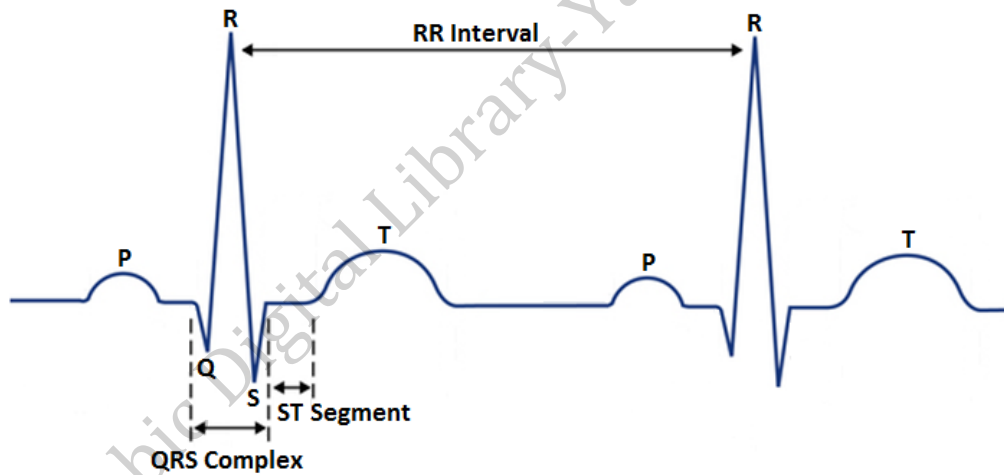


Figure 1: Components of FECG signal.

The waveforms of the fetus heart can help in the diagnosis of fetus heart arrhythmia such as congenital heart disease, bradycardia, asphyxia, tachycardia and hypoxia. Changes in the RR intervals (i.e. is the interval between QRS complexes) provide useful information to detect any change in the fetus heartbeats (Oudijk, 2003).

Therefore changes in the fetus heartbeats are associated with cardiac disease. Thus, it is important to assess fetus heart in early stages to take appropriate precautions.

1.2 Background Information

Assessment of the fetus heart health during pregnancy requires FECG signal which is taken from the abdomen of a pregnant woman. This signal has a very low Signal to Noise Ratio (SNR). Any small noise in the FECG signal can change the characteristic of the signal; therefore, the noise must be removed. In this study, bandpass filter is used to reduce the noise from the abdomen signal.

Bandpass filter is designed using low-pass and high-pass filters. Low-pass filter passes signals that have frequency lower than a specific cutoff frequency, while attenuates signals that have higher frequency. High-pass filter is the opposite of low-pass filter. High-pass filter design is based on the output of the first-order low-pass filter which is subtracted from the all-pass filter (Kasar, Mishra and Joshi, 2014).

The abdominal signal contains two independent signals; the mother cardiac signal and the fetus cardiac signal. FastICA is a technique used to extract FECG signal from the abdominal signal. The method decomposes a measured signal into a set of independent signals without prior knowledge about the sources that generate the signals. It is assumed that the measured signal is a convolution of independent signals. FastICA aims to estimate the independent source signals (Luo, 2012).

Heart Rate Variability (HRV) signal describes the variation between every two consecutive R peaks. It is used to predict potential complications for the fetus during pregnancy. HRV analysis methods can be classified into nonlinear methods, time-domain methods and frequency-domain methods. In nonlinear methods, sequences of RR intervals are recognized as the nonlinear system outcome. Time-domain methods use short-term

variability or long-term variability. Short-term variability indicates rapid changes in Heart Rate (HR), while long-term variability represents slower fluctuations. Frequency-domain methods concern to recognize HRV at frequency ranges associated with particular physiological process. Analysis of HRV using frequency-domain methods requires resampling the sequence of RR intervals in order to make it a regularly sampled signal. The frequency-domain analysis assumes that it cannot satisfy steady state process since RR intervals are changed over time. Thus, there is a need to estimate the RR intervals at specific points. To do so, interpolation algorithms are applied to the RR intervals. These algorithms are Lagrange Interpolation, Linear Interpolation, Cubic Spline Interpolation and Hermit Interpolation. In this study, Cubic Spline Interpolation is used, which divides a given interval into subintervals. On each subinterval, a different approximating polynomial is constructed (Jang et al., 2012). The method is the widely used for the RR interval fitting than the other methods and in this problem it shows the lowest error rates in the calculation of the HRV signal.

The Dual-Tree Complex Wavelet Transform (DTCWT) is proposed by Kingsbury in 1998 (Kingsbury, 1998) to overcome the drawbacks of Discrete Wavelet Transform (DWT). DWT suffers from lack of shift invariance due to the operation of down sampling at each level. The dyadic filter tree is used as a solution for providing nearly shift invariant signal. However, the solution suffers from high redundancy in the output; hence the computation requirements are increased.

DTCWT employs two trees, each one uses a different set of filters. The trees give the real and imaginary parts of the complex wavelet transform. DTCWT with shift invariant and directional selectivity properties make the transform useful in signal analysis

application. Two DWTs are used in parallel to implement the DTCWT of a signal. The filters are designed to interpret the real part of a complex wavelet transform via upper DWT sub-band signals and imaginary part of a complex wavelet transform via lower DWT sub-band signals. This design makes the DTCWT nearly shift invariant (Kingsbury, 1998; Thomas, Das and Ari, 2014).

Support Vector Machine (SVM) is presented by Vapnik for binary classification (Cortes and Vapnik, 1995). SVM has been used in many applications such as signal processing, image processing, handwriting digit recognition and face detection (Borole and Sapkal, 2013). The basic idea of SVM is to find the hyperplane that separates the samples into two classes perfectly (Kalaiselvi *et al.*, 2016). When the samples are close to the hyperplane, the rate of classification is not very high. The vectors near to the class boundaries are support vector and the distance between hyperplanes and support vector is called the margin (Pitale, Tajane and Umale, 2014).

In this thesis, a method for assessing the health of the fetus heart during pregnancy is proposed using abdominal signal noninvasively. The abdominal signal is contaminated by noise and baseline wander and a convolution of FECG and MECG. First; the noise is removed by using bandpass filter while baseline wander is corrected by subtracting the best-fit line from the abdominal signal to get higher SNR. Second; FastICA technique is applied to extract FECG signal, which can separate a source signals from a mixed signal (i.e. can separate MECG and FECG from the abdominal signal), then the MECG signal and any other signals are suppressed to extract the FECG signal. Third; R peaks are extracted from the FECG signal and the sequence of RR intervals are calculated in order to construct the HRV signal using Cubic Spline Interpolation method. Fourth; from the HRV signal

important features are calculated using DTCWT. Finally; the features that are obtained from the HRV signal are given as input to SVM classifier to classify the status of the fetus heart and deliver a report about the conditions, which can be used by a physician as a decision support tool.

1.3 Research Purpose

FECG signal records the electrical activity of fetus heart and provides valuable information about its performance. The signal has a very low SNR due to the overlap of MECG and noise. So, there is a need to suppress the MECG signal and noise signals to get a clean FECG signal. Then, FECG signal can be processed to extract important information to detect any irregularity in the fetus heart. The aim of this study is to develop a method that:

- Separate the FECG from MECG signal.
- Detect R peaks from the FECG signal.
- Construct the HRV signal using a cubic spline interpolation.
- Extract a set of representative feature from the constructed HRV signal for the FECG signal.
- Classify the status of fetus cardiac health and generate a report for decision support.

1.4 Research Motivation

One out of 100 babies is born with heart disease every year in Jordan (about 1780 babies). Monitoring the fetus heart signal can provide information about the fetus cardiac condition. This information can determine the fetus life, development and heart disease. Any abnormality in this signal may mean that the fetus is at risk (e.g. insufficient amount of oxygen).

The early detection of abnormal FHR can help pediatric cardiologist to suggest appropriate medication in time and take precautions during or after birth. Therefore, there is a need to periodically monitor the fetus heart to extract information about the health of the fetus during pregnancy. Our goal in this study is to develop a method that provides information about the fetus cardiac health to reduce irrevocable conditions.

1.5 Research Questions

The characteristic of the FECG signal differs from adult ECG signal. The FHR is higher than the HR for adults, and the fetus HRV signal is less stationary than the adult HRV signal. The FECG have weaker amplitude than that of the MECG due to the source of the signal, which is usually small (i.e. fetus heart). So, it is difficult to detect FECG waves.

This study achieves the assessment of the health and condition of the fetus heart, and answers the following questions:

- How to denoise the abdominal signal?

- How to extract the FECG signal from the abdominal signal?
- How to detect the fetus R peaks?
- How to construct the fetus HRV signal?
- How to classify the constructed HRV signal?

1.6 Research Significance

Abdominal signal acquisition, abdominal signal preprocessing, FECG signal extraction, HRV signal construction, features extraction and classification are the major steps of the proposed method to detect the normality of fetus cardiac health. The proposed method classifies an FECG signal to normal or abnormal using DTCWT coefficients. DTCWT provides nearly shift invariant property; its coefficients can distinguish the shifting in the input signal. Also, it provides directional selectivity property, these properties are useful in signal processing applications and decrease the computational requirements compared with the traditional wavelet transform. In this study, DTCWT is used to decompose the HRV signal and extract informative features to characterize the condition of the fetus heart.

1.7 Limitation of the Scope

- This method is applied on the pregnant woman in 20 weeks of gestation or more.
- The method cannot be used during delivery.

- Abdomen signal with sampling rate greater than $250Hz$ is needed, to cover all the devices frequencies that are available in the hospitals.
- The proposed algorithm can be used on mothers pregnant with only one fetus, because the algorithm cannot be applied on twins fetal.

1.8 Thesis Outlines

The rest of the thesis is organized as follow: Chapter two reviewed the literature. In chapter three the proposed methodology is presented. Chapter four illustrates the implementation of the proposed method. The experimental results are reported in chapter five. Finally, the conclusions are provided in chapter six.

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Chapter 2

Literature Review

2.1 FECG Extraction Methods

Abdominal ECG signal consists of different signals; FECG, MECG and interference signals. It is important to find a method to extract the FECG signal only. Different methods are applied to extract the FECG signal from the abdominal signal like Adaptive Filters, Blind Source Separation (BSS), Neural Network and Wavelet Transform. The following subsections provide a literature review about each method.

2.1.1 FECG Extraction using Adaptive Filter

(Shadaydeh, Xiao and Ward, 2008) use Adaptive Volterra Filter (AVF) to extract FECG signal from MECG from one thoracic signal and one or more abdominal signals. In the case where one abdominal signal is used, the algorithm uses the Adaptive Noise Canceller (ANC) to estimate the FECG signal. But where more than one abdominal signal is used the algorithm uses Liner Combiner (LC) to compose a primary noise signal, then the Recursive Least Squares (RLS) algorithm is used to update the AVF and the LC parameter to estimate the FECG signal. When more than one abdominal signal is used the FECG signal extracted better than when one abdominal signal is used and the MECG signal removed completely.

(Swarnalatha and Prasad, 2010) propose three methods to extract FECG from the Abdominal signal based on multi-stage adaptive filtering which combine the filters using RLS, Least Mean Square (LMS) and Normalized LMS (NLMS):

- FECG extraction method: the abdominal signal preprocessed by separating high-resolution components from low-resolution components. The noise signal derived and removed from the abdominal signal. The signal reconstructed using Inverse Fast Fourier Transform (IFFT). Then this signal is used to improve the non-linear parameter of the filter. Modify the thoracic signal by scaling, squaring and scaling to use it with the non-linear parameter as the input to the multi-stage adaptive filtering to isolate the MECG signal.
- Improved FECG extraction method: to improve the quality of the extracted fetus signal, refinement is proposed after extract FECG signal. This method gives a better result than the previous method.
- Novel method of FECG extraction: after preprocessing stage multiplies the denoising signal by factor k and avoid the refinement after the extracted FECG. This method gives better FECG signal compared with method 1 and method 2. The combination of RLS and LMS gives a better result, thus, the three proposed methods used this combination.

(Prasanth, Paul and Balakrishnan, 2013) implement a method used ANC to remove MECG and digital filters to remove high frequency. FECG is extracted from RR interval by set of dynamic thresholds and count any signal passes the threshold. From simulation results, it is clear that the FECG signal extracted from the abdominal signal successfully.

(Kahankova, Martinek and Bilik, 2017) introduce RLS based Finite Impulse Response (FIR) adaptive filter to extract FECG signal. The proposed system used the abdominal signal as a primary input and thoracic signal as a reference signal. The thoracic signal is considered as noise in this algorithm and is subtracted from the primary signal so that the FECG signal is the back propagated error signal. The RLS adaptive filter is compared with Fast Transversal Filter (FTF), RLS filter outperforms the FTF filter which is not suitable for FECG signal extraction.

2.1.2 FECG Extraction using Blind Source Separation

(Sato et al., 2007) propose a novel method to extract FECG signal based on BSS which consists of the removal of MECG signal and BSS with Reference (BSSR) signal. MECG signal is canceled by subtracting the combination of heart vector projections from the abdominal signal in each electrode. Prewhitening is performed to remove the effect of the noise. Then Independent Component Analysis (ICA) and BSSR are performed to extract the FECG signal. This method is for online processing and requires a greater number of electrodes. In addition, some other source will be used to take the reference signal.

(Camargo-Olivares et al., 2011) present a system to extract FECG using Multidimensional ICA (MICA). The system uses FIR bandpass filter to remove the electromyography noise and baseline wander, and notch filter to remove the power line interference to preprocess the abdominal signal. Then estimate the MECG signal by filtering the abdominal signal and Principal Component Analysis (PCA) is used. The

preprocessed abdominal signal and the estimated MECG signal are used as the input to ICA in order to perform MICA and extract FECG signal. Then, the extracted signal is filtered to increase the SNR. The proposed approach fails when the residual noise is stronger than FECG signal.

(Ghazdali et al., 2015) present a new method of BSS, the idea is to use the bilateral filter to remove the noise from the abdominal signal and BSS to extract the FECG signal by minimizing the divergence of the Kullbak-Leibler between copula densities. The proposed method outperforms the ICA method.

(Petrolis, Gintautas and Krisciukaitis, 2015) propose multistage PCA to extract components of the abdominal signal. PCA algorithm is applied on the abdominal signal, which constructs MECG signal, then subtract this MECG signal from the abdominal signal. After subtraction of MECG signal, PCA method is used to separate FECG signal from the rest of the abdominal signal. But this is performed using arrays of all abdominal signal samples after subtracting MECG signal from them. Finally, FECG signal is reconstructed using PCA algorithm. The proposed method is achieved 77% sensitivity, 62% specificity and 71% accuracy.

(He and Chen, 2016) separate FECG signal using single channel BSS algorithm. The algorithm decomposes the abdominal signal into a set of Intrinsic Mode Function (IMF) using Empirical Mode Decomposition (EMD). Eigenvalue method is used to estimate independent components number. Then the separation is achieved by non-negative matrix factorization, which is constructed according to the number of independent components and decomposed IMF. The advantage of this method is that it uses only one

abdominal signal, while the other methods require multiple numbers of the abdominal signal. Furthermore, this method could determine multiple fetuses not only to one fetus.

(Ionescu, 2016) extract FECG signal based on FastICA algorithm, the proposed method used high pass FIR filter, notch filter and Butterworth bandpass filter to cancel the noise from abdominal signal and FastICA algorithm is used to extract FECG signal. To enhance the quality of FastICA extraction method, the undecimated wavelet transform is used in order to remove noise from the extracted FECG signal. A combination of multiscale peak detection and peak detector is used for feature extraction from FECG signal. The results show that FECG signal can be successfully extracted from a set of abdominal signals.

2.1.3 FECG Extraction using Neural Network

(M. A. Hasan, Ibrahimy, et al. 2009a) use neural network to isolate the FECG signal from the abdominal signal. In this method, MECG signal is considered as the input signal and the abdominal signal is the target signal. By using this approach, the MECG signal has been removed from the abdominal signal by correlation detracton. So, FECG signal is considered as the only input. This technique works correctly on high learning rate which is close to 1 and low momentum value equal to 0.2.

(Golzan *et al.*, 2009) present an approach to extract FECG using neural network. The proposed approach use coefficients of Fast Fourier Transform (FFT) to extract the features from the abdominal signal. To reduce features dimensionality, PCA is used. These

features are the input to the Artificial Neural Network (ANN). This approach uses multi-layer perception ANN with Bayesian approach for the classification. The moderated outputs of the Bayesian add computational overhead and could not enhance the neural network. The presented approach can achieve high accuracy and reliable detection.

(Amin, Hashim and Husain, 2011) use adaptive linear neural network to separate the FECG signal from the abdominal signal. The MECG enters the network and passes through delays, the output of the delays multiplied by the initial weight. After that, the output passes through the linear transfer function. Finally, the FECG signal extracted by subtracts the network output from the abdominal signal. From simulation results, when high value of learning rate, low value of momentum and small value of initial weights are used the proposed method will produce good results.

(Ma et al., 2014) propose a nonlinear ANC based on the Function Link ANN (FLANN) to extract FECG signal. This system requires one abdominal channel and multiple thoracic channels each channel has one FLANN and FIR filter. ANC use the abdominal signal as the primary signal and MECG signal as the reference signal. LMS algorithm is used to update the FIR filters and the FLANN coefficients, which are the components of ANC system. FLANN has many properties such as computational efficiency and fast convergence. The proposed system is effective and outperforms the ANC with FIR filters.

2.1.4 FECG Extraction using Wavelet Transform

(Desai and Sankhe, 2012) extract FECG signal based on multi-scale DWT. Digital bandpass filter is applied to remove the noise from the abdominal signal. To extract the QRS complex from the signal DWT is used, which decompose the signal into low-pass and high-pass filters. Low-pass filters give approximation coefficients, while high-pass gives detail coefficients. This system can detect all fetus heartbeats correctly in five minutes of recording.

(Immanuel et al., 2012) use wavelet transform to remove the noise from the abdominal signal. Then Lifting Wavelet Transform (LWT) decomposition is used to decompose the signal in time-frequency domain. FastICA algorithm is applied to the decomposed signal to separate the FECG signal and the MECG signal. Finally, the inverse LWT is used to reconstruct the separated signals. FastICA in this approach has the best SNR for FECG signal and MECG signal compared with ICA, fixed-point ICA and equivariant robust ICA.

(Bsoul, 2015) implement a method based on wavelet transform to extract FECG signal. This method works as follows: remove the noise from the abdominal signal by using bandpass filter. Then, decompose the filtered signal using wavelet transform, which performed by Haar mother wavelet at level 2. Finally, derive the coefficients and apply a threshold operation to extract FECG signal. This method has been tested on five records, each record for half an hour. The average accuracy for all records is 92.1%.

2.1.5 Hybrid Techniques

(Kezl Selva Vijila and Kanagasabapathy, 2008) propose Adaptive Neuro Fuzzy Inference System (ANFIS), which combines neural network and fuzzy logic technique. The proposed technique requires two signals one from the abdomen and the other from the thoracic to extract FECG. ANFIS extracts the MECG from the abdominal signal. The ANC is used to estimate the FECG signal by subtracting the extracted MECG from the abdominal signal. This technique has less convergence time compared with neural network due to the use of fuzzy logic for decision making and verification.

(Luo, 2012) propose a combination of BSS and EMD to extract FECG signal from abdominal signal. The FECG signal is extracted using recursive least squares BSS method. EMD is used to remove the noise from the extracted FECG signal and estimate the final FECG signal. The proposed algorithm is compared with FastICA. The convergence speed of the proposed algorithm is fast since it does not require demean and whitening.

(Kumar, Sharma and Prasad, 2013) suggest ANFIS system to extract FECG using two signals, thoracic signal and abdominal signal. The thoracic signal is passed through neuro-fuzzy filter to cancel the noise from the thoracic signal and the same signal passed through non-linear transform found by the ANFIS network that operates on the thoracic signal and the abdominal signal. The output of the ANFIS is subtracted from the noisy abdominal signal to extract the FECG signal. The wavelet transform is used to improve the FECG signal.

(Wu et al., 2013) present a combination of wavelet analysis, LMS adaptive filtering, and the Spatially Selective Noise Filtration (SSNF) algorithms for FECG extraction.

Stationary Wavelet Transform (SWT) is used to process abdominal signal and thoracic signal to obtain the coefficients of the wavelet at each scale. LMS algorithm processes the detail coefficients at each scale, the original input of the LMS is the abdominal signal coefficient and the reference input is the thoracic signal. SSNF algorithm is used to set the threshold and remove the noise. Coefficients of the processed wavelet were reconstructed to extract the FECG by inverse SWT. This approach outperforms the LMS adaptive filtering algorithm.

(Kumar, Sharma and Prasad, 2016) extract FECG signal by using wavelets and neuro-fuzzy systems. The proposed system requires two signals; the thoracic signal (MECG signal) and the abdominal signal. The MECG signal after its generation is passed through nonlinear transform. The same MECG signal is going through the neuro-fuzzy system and filtered to remove noise and get a clean MECG signal. In the proposed system, ANFIS network use thoracic signal and abdominal signal as an input. Then, the output of the ANFIS system is subtracted from the abdominal signal to obtain the FECG signal. To enhance the extracted FECG signal, wavelet transform is used. This method outperforms Singular Value Decomposition (SVD), BSS, ICA and ANFIS in terms of SNR. A summary of the previous literatures review for the FECG extraction methods are summarized in Table 1.

Table 1: Review table for adaptive filter, blind source separation, neural network, wavelet transform and hybrid techniques of FECG signal extraction methods.

Method	Authors & Year of Publication	Notes
Adaptive Filter	(Shadaydeh, Xiao and Ward, 2008)	When the proposed algorithm uses more than one abdominal signal it extracts FECG signal and removes completely the MECG signal better than when using one abdominal signal.
	(Swarnalatha and Prasad, 2010)	Proposed three methods based on multistage adaptive filtering; FECG extraction method, improved FECG extraction method and novel method of FECG extraction. The last one has best position predictivity, sensitivity and accuracy. The advantage of this method is that it requires one abdominal signal and one thoracic signal.
	(Prasanth, Paul and Balakrishnan, 2013)	A new approach based on adaptive filter is proposed. The results show that the FECG signal can be extracted from the abdominal signal successfully by using LMS algorithm for ANC system implementation.
	(Kahankova, Martinek and Bilik, 2017)	Proposed RLS based FIR adaptive filter, the proposed technique outperforms FTF filter, since it has best SNR percentage root-mean-square difference and root-mean-square error values than FTF filter.
Blind Source Separation	(Sato <i>et al.</i> , 2007)	The proposed method able to extract the P, T and R waves successfully. The accuracy and reliability of the extracted FECG signal were confirmed by comparing it with a signal recorded from the scalp of the fetus.
	(Camargo-Olivares <i>et al.</i> , 2011)	Present a system using MICA. This system estimates the MECG signal then inputs this signal to MICA. From the experimental results, the proposed system outperforms the traditional approach. But it fails when the residual noise is stronger than FECG signal.

	(Ghazdali <i>et al.</i> , 2015)	Present a new method of BSS, this method isolates FECG signal from the abdominal signal without any loss of information in comparison with the ICA.
	(Petrolis, Gintautas and Krisciukaitis, 2015)	Suggest multistage PCA algorithm to extract FECG signal. Authors depend on the energy of FECG signal since this signal has less energy than other components of the abdominal signal. Firstly, PCA is applied which construct MECG signal that has higher energy than FECG signal to subtract this signal from the abdominal signal. Then the energy of FECG signal exceeds the energy of other components. After that, PCA is applied one more time to extract FECG signal. Accuracy for this algorithm is 71%.
	(He and Chen, 2016)	Proposed signal channel BSS algorithm. This algorithm is suitable for multiple fetuses and can extract EFECG signal from the abdominal signal accurately.
	(Ionescu, 2016)	FastICA algorithm is used for FECG signal extraction. The proposed algorithm can extract the signal successfully. FFT and IFFT are very useful for weak FECG signals.
Neural Network	(M A Hasan <i>et al.</i> 2009a)	Proposed neural network for FECG signal extraction. This approach works correctly on high learning rate which equals to 1 and low momentum value which equal to 0.2.
	(Golzan <i>et al.</i> , 2009)	This method uses FFT to extract the feature from the abdominal signal, PCA to reduce feature dimensionality and these features are given as ANN input. Bayesian approach adds computational overhead and does not improve the neural network predictions. The proposed method extract FECG signal in high degree of accuracy.
	(Amin, Hashim and Husain, 2011)	Extract FECG signal from the abdominal signal using adaptive linear neural network. The proposed algorithm gives good results when it uses low value of momentum, high value of learning rate and small value of initial weights.

	(Ma <i>et al.</i> , 2014)	Proposed nonlinear ANC method based on FLAAN for FECG signal extraction. ANC use the abdominal signal as the primary signal and MEEG as the reference signal. There are many properties of FLANN such as computational efficiency and fast convergence.
Wavelet Transform	(Desai and Sankhe, 2012)	This method used DWT which provides at high-frequency good time resolution and at low frequency better frequency resolution. The proposed method can extract all fetus beats correctly.
	(Immanuel <i>et al.</i> , 2012)	LWT is used to decompose the abdominal signal and FastICA to separate the FECG signal and MEEG signal from the decomposed signal. FastICA in this approach has the best SNR in comparison with ICA, fixed-point ICA and equivariant robust ICA.
	(Bsoul, 2015)	DWT is used to decompose the abdominal signal. The proposed method has been tested on five standard records, the average of the accuracy for all five records is 92.1%.
Hybrid Techniques	(Kezl Selva Vijila and Kanagasabapathy, 2008)	ANFIS takes the advantages of neural network and fuzzy logic technique. Fuzzy logic technique is used for decision making and verification, thus converges speed will be fast. This technique has higher SNR, less noise in the extracted FECG signal and less convergence time compared with neural network.
	(Luo, 2012)	A combination of BSS and EMD is proposed. From the experimental results this algorithm extracts FECG signal efficiently and can greatly remove noise. The convergence speed of the proposed algorithm is fast compared with FastICA because this algorithm does not require demean and whitening.

	(Wu <i>et al.</i> , 2013)	Combined SWT, LMS adaptive filtering and SSNF algorithms. SWT is used to obtain the coefficients at each scale. To process detail coefficients, LMS adaptive filtering is used. SSNF algorithm for noise removal. This technique gives results better than LMS adaptive filtering algorithm.
	(Kumar, Sharma and Prasad, 2016)	ANFIS with wavelet transform is proposed to extract FECG signal. The proposed system requires only single channel abdominal signal and can be implemented in real-time systems. ANFIS is used to extract FECG signal and wavelet transforms to enhance the extracted signal and get a clean FECG signal. This method has higher SNR than SVD, BSS, ICA and ANFIS algorithms.

2.2 Heart Rate Variability

(Padmanabhan et al., 2007) present a technique that generates HRV sequences from ECG signals. The proposed technique use bandpass filter to remove baseline wander. Daubechies wavelet is used to decompose the signal at level five for noise removal from ECG signal. For QRS detection in this technique, a threshold and derivative approach are used. The ectopic beats are identified to isolate it and remove adjacent beats to them, the RR intervals are found using the detected peaks. From simulation results, the proposed technique gives high specificity and sensitivity. Also, it tested on ambulance data and it gives good results, but it suffers from high level of noise due to the ambulance motion and patient movement.

(Lweesy et al., 2009) propose a new method for the FHR and the fetus HRV extraction. The proposed method determines the fundamental and the higher frequencies harmonics of the MECG signal, which are calculated from the abdominal signal directly.

Then the notch filter is used to remove the harmonics, and a bandpass filter is used to determine the fundamental frequency of the FECCG signal. The inverse Fourier transform is applied to the filtered signal to represent the RR intervals. As in the simulation results, HR and HRV can be detected successfully from the ECG records.

(Piotrowski and Rózanowski, 2010) present method for detect HR and another method for HRV estimation in ECG signals for military aircraft flights purpose. Short-term autocorrelation center clipping approach is used to detect R-peaks from ECG signal. This method is used for biological signal detection in noisy environment. While power spectral density is used for HRV estimation based on non-parametric and parametric methods. This method is powerful against additive noise and artifacts, and effective to detect quick ECG beats.

(Costin, Rotariu and Păsărică, 2012) use HRV for detecting mental stress from ECG signals. For signal preprocessing a bandpass filter is used for baseline wander removal, then to remove the noise from ECG signal a median filter is used. The dynamic time warping is used as normalization procedure to align a QRS complex to the next and previous two QRS complexes. The Pan-Tompkins method is used to detect the R-peaks and QRS complex length. For HRV analysis, this method uses time domain and frequency domain analysis. In time domain analysis, this method uses mean HR and mean RR interval measures of the RR time sequences. While in frequency domain, HRV measures are extracted from the spectral components of the RR interval time sequence, these components are obtained by applying FFT. Finally, separability index is used in order to evaluate HRV measure performance. The proposed technique is better than the traditional one; it can detect and evaluate the

status of the human in an effective way. The accuracy of this technique is approximately 90%.

(Simegn, Kassaw and Addis, 2015) propose a technique that analyzes the FHR. First, this technique is preprocessed the signal using wavelet denoising to reduce the noise, Butterworth low-pass filter to remove the baseline wander and Savitzky-Golay filter and notch filter to extract power line interference. Second, a combination of Hilbert transform, bandpass filter and adaptive thresholding are used to detect the MEEG signal and remove it. Third, analyze the FHR as follows: determine the intervals between R-peaks, if the detected peak is the first one, the RR interval is set to 0 and remove the duration count of first peak and the rest peaks, the distance between any two peaks will be equal to the new index minus the old index of peak detection. Then all of the RR intervals are determined. This technique has been tested on 20 records and the results indicate that the proposed technique has promising results.

A summary of the previous literature review for the HRV methods are summarized in Table 2.

Table 2: Review table for heart rate variability methods.

Authors & Year of Publication	Notes
(Padmanabhan et al., 2007)	High value of specificity and sensitivity will be achieved by using the proposed technique. The main advantage of this technique is the ability to use it on ambulance ECG data, which gives good results.
(Piotrowski and Rózanowski, 2010)	The presented approach is for military aircraft flights purpose. This technique can detect quick ECG beat in efficient way, also can estimate HRV signal in huge amount of noise.

(Costin, Rotariu and Păsărică, 2012)	Implement a method for HRV signal construction and analysis. This method is effective to detect and evaluate the human state, it has better results than the traditional analysis and the results gives a high accuracy which is approximately 90%.
(Simegn, Kassaw and Addis, 2015)	The presented approach is simple, effective and automatic. Also, can be used in non-clinical environment, which can be used by the mothers themselves. From the simulation results this approach has promising results.

2.3 Conclusion

By the review for previous literature, we can realize that:

- Adaptive algorithm is accurate method to detect FECG and MECG signals from the abdominal signal with low computational complexity.
- Wavelet transform is effective and flexible tool to extract FECG signal and remove MECG signal. Also, it is effective tool for denoising, the denoised signal is reconstructed by the inverse of the wavelet transform.
- Wavelet transform requires one abdominal signal to eliminate the MECG signal and extract FECG signal from the abdominal signal.
- ANN is very fast technique, but sometimes the exact baseline value it does not estimate.
- BSS is efficient and fast approach and gives high SNR.
- In BSS there is no prior knowledge about the source that generates the signals.
- To reach reliable FECG signal in BSS often a large number of electrodes are required.

- Wavelet transform obtained high specificity and sensitivity for HRV analysis.
- In noisy environments, shot-term autocorrelation center clipping approach is the best one for construct HRV signal.

In order to assess cardiac fetus health during pregnancy and to get the advantages of previously listed approaches, this thesis present a method that:

- Assess the fetus cardiac health based on Blind Source Separation method to extract FECG signal from the composite abdominal signal.
- Construct the Heart Rate Variability signal from the extracted FECG signal using Cubic Spline Interpolation method.
- Extract some features from the Heart Rate Variability signal using Dual-Tree Complex Wavelet Transform coefficients.
- Use Support Vector Machine to classify the extracted features and identify if the fetus is healthy or not.

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Chapter 3

Research Methodology

In this chapter, a new method for fetus cardiac health assessment is presented. The first step is preprocessing step, which aims to remove the noise and baseline wander from the mother's abdominal signal. The second is to suppress the MECG signal from the abdominal signal to get a clean FECG signal. In the third step, the HRV signal is constructed to extract the features from it using DTCWT and detect if there is any abnormality in the fetus cardiac functions. Figure 2 represents the workflow of the proposed method in this thesis and the following subsections illustrate these steps.

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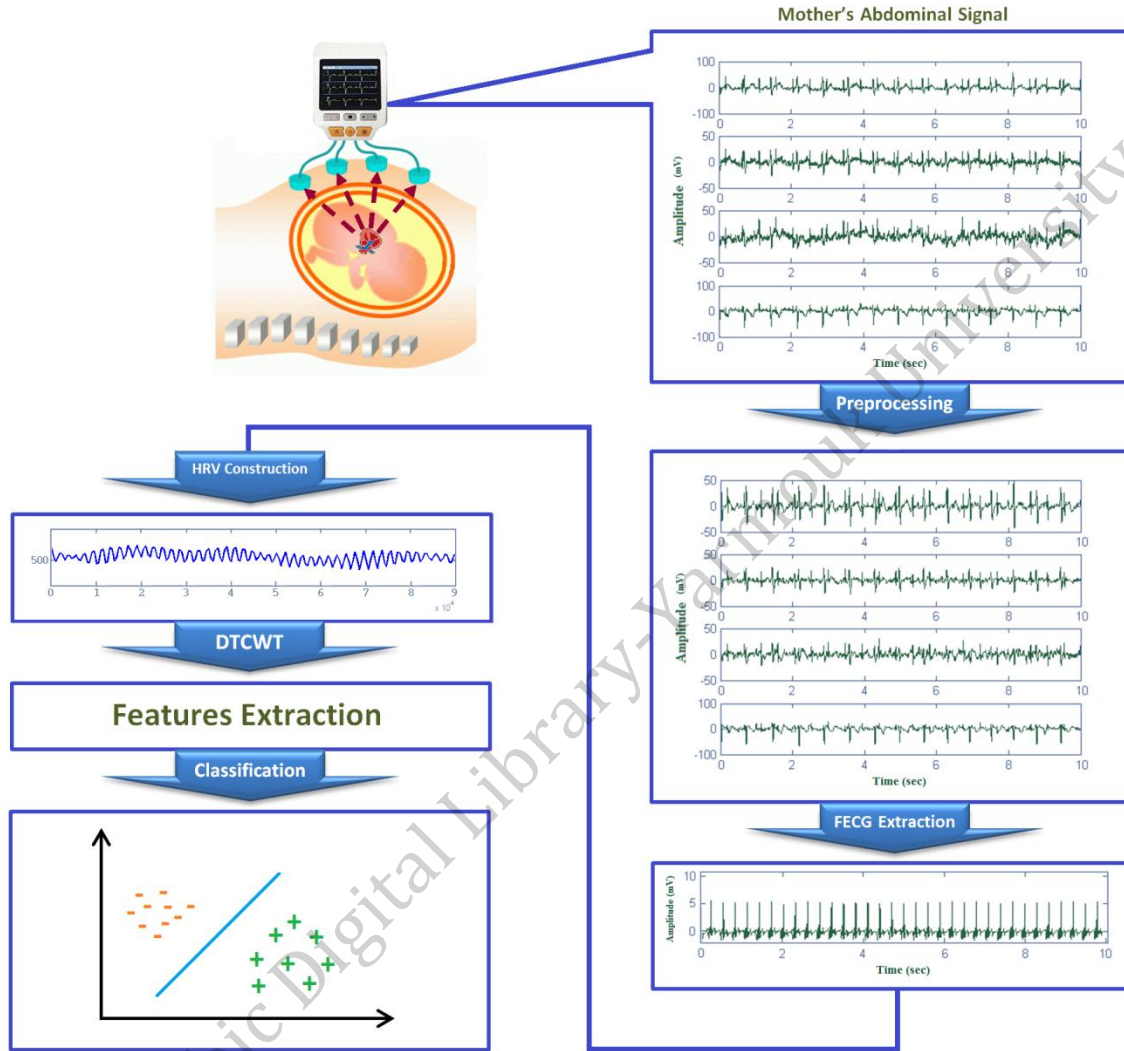


Figure 2: The framework of the proposed approach.

3.1 Research Phases

Figure 3 illustrates the main steps to process the abdominal signal that is recorded from a pregnant woman.

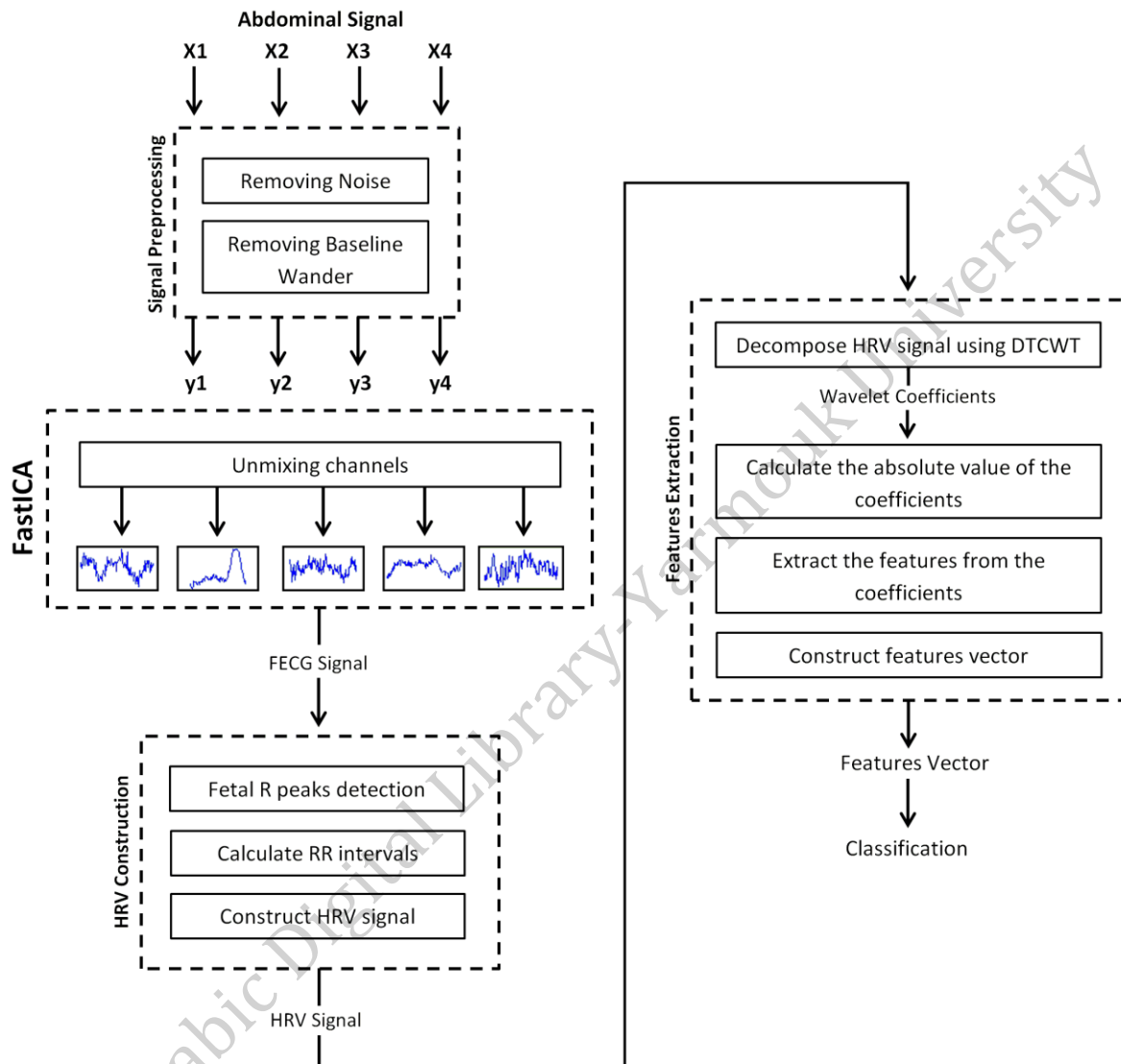


Figure 3: Main steps of the proposed method.

3.1.1 Signal Preprocessing

FECG signal is obtained from the mother's abdomen to diagnose the condition of fetus health. The FECG signal is contaminated by noise, baseline wander and MECG signal. The noise significantly corrupts the FECG signal and reduces the SNR. Also, the structure and shape of the FECG signal depend on the electrodes position, gestation age and

fetus position (M. A. Hasan et al. 2009b). All of these constraints make the extraction of FECG signal a difficult process. To preprocess the FECG signal, there are two main steps: noise attenuation and baseline wander removal. The following subsections show how these noises are removed.

3.1.1.1 Noise Attenuation

The FECG signal is covered by several sources of noise such as power line interference, muscle contractions and electromyogram. This noise is the main limitation of FECG recording as well as the low amplitude signal for the fetus heart and skin potentials. Some methods of signal processing can detect QRS complex, but some remain hidden. This is due to low SNR. Bandpass filter is a fast and real-time recursive filter. The main characteristic of the bandpass filter is its ability to attenuate all frequencies that are outside a specific band at -3dB under the maximum bandpass gain. This band of frequencies is set between lower frequency and higher frequency. The two frequencies are called cut-off frequency, that attenuate any signals outside this range while passes any signals inside of these two frequencies. The difference between lower frequency and higher frequency is called bandwidth of the bandpass filter as shown in Figure 4. To remove noise from the abdominal signal, this research uses bandpass filter with cutoff frequency between $0.5Hz$ and $49Hz$ based on the Fourier transform to emphasize the fetus signal and remove the noise signals.

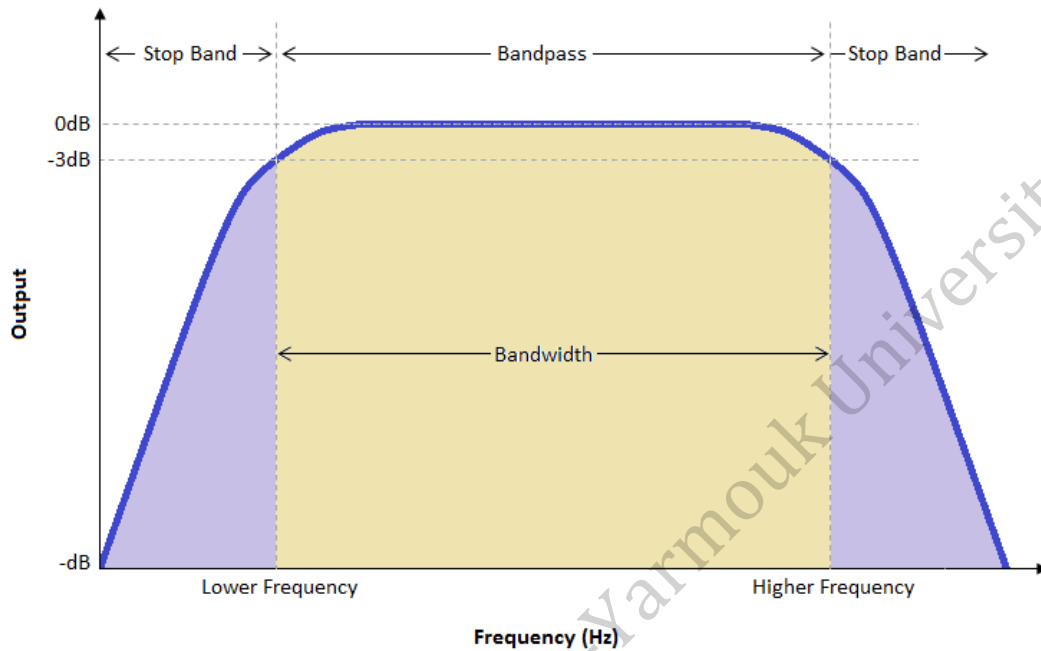


Figure 4: Frequency for the bandpass filter.

3.1.1.2 Baseline Wander Removal

Baseline wander is one of the main sources of noise that are added to the FECG signal as a sinusoidal component due to respiration or patient movement. Respiration varies the ECG signal amplitude by about 15% (Hasan *et al.*, 2009b). The upper limit of the baseline wander is less than 1Hz during normal breathing. If any exercise is being performed, the upper limit may be increased. The fetus motion also changes the baseline. It adds a sine wave with one cycle having a duration between 100 – 500ms and a frequency between 2 – 10Hz (Lamesgin, 2014). This research removes the baseline drift by subtract best-fit line from the abdominal signal.

The equation of the best fit line is given by (Bsoul, 2011):

$$y = mx + b \quad (1)$$

Where y : point in the line.

m : is the line slop.

b : is the intercept.

The line slop and intercept are calculated as in Equation (2) and Equation (3) respectively (Bsoul, 2011).

$$m = \frac{n(\sum_1^n xy) - (\sum_1^n x)(\sum_1^n y)}{n(\sum_1^n x^2) - (\sum_1^n x)^2} \quad (2)$$

$$b = \frac{(\sum_1^n y) - m(\sum_1^n x)}{n} \quad (3)$$

3.1.2 FECCG Signal Extraction

After removing noise and baseline wander, the next step is to suppress the MECCG signal from the abdominal signal to extract the FECCG signal. This research uses blind source separation method, FastICA, in order to separate MECCG signal and FECCG signal from the abdominal signal. FastICA is an important method in signal processing field that aims to separate source signals from a mixed signal (Hyvärinen and Oja, 2000). It is fast and requires little memory space and computation requirements. This method finds the unmixing matrix that represents independent components (Ionescu, 2016). The basic steps for FastICA algorithm are as follow (Hyvärinen and Oja, 2000):

Step 1: choose a random ω , which is the weight vector.

Step 2: find ω , where $\omega = E\{xg'(\omega^T x)\} - E\{g''(\omega^T x)\} \omega$.

Step 3: normalize ω , by $\omega' = \omega / |\omega|$.

Step 4: if ω' does not converged, go back to step 2.

Where ω : weight vector, which represents one column of the estimated inverse of the mixing matrix.

ω^T : the transpose of ω .

E : orthogonal matrix.

x : observation after whitened and centered data.

g' : the contrast function derivation.

g'' : the second derivation of the contrast function.

The previous steps estimate only one independent component. To estimate more than one independent component, several neurons are used to run FastICA with weight vectors $\omega_1, \omega_2, \dots, \omega_n$, where n is the number of iterations. As well as the outputs $\omega_1^T x, \omega_2^T x, \dots, \omega_n^T x$ must decorrelate after every iteration to prevent vectors from converging. Figure 5 shows the process of FECG signal extraction, and the main steps of FastICA method are illustrated in Figure 6.

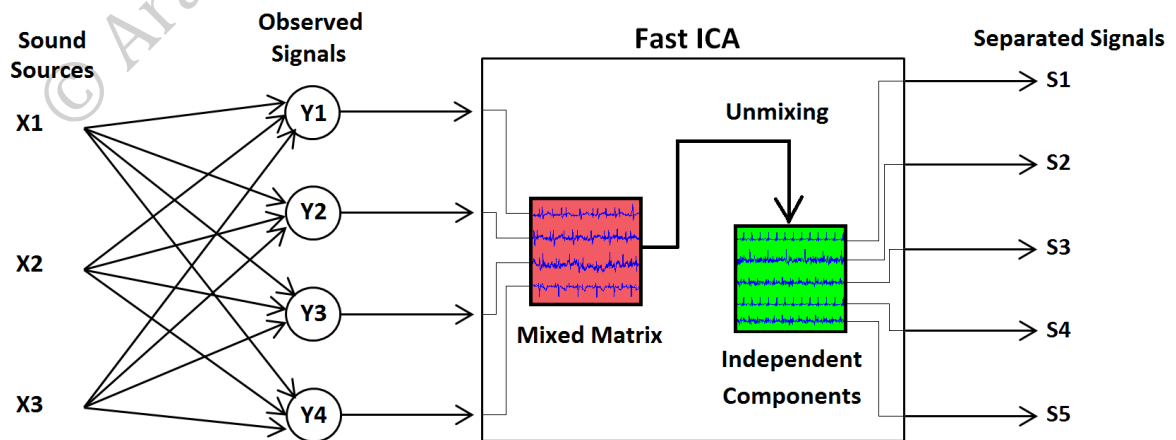


Figure 5: FastICA block diagram, where x is the sources of the sound, y is the observed signals and s present the independent component, which is the output of the FastICA method.

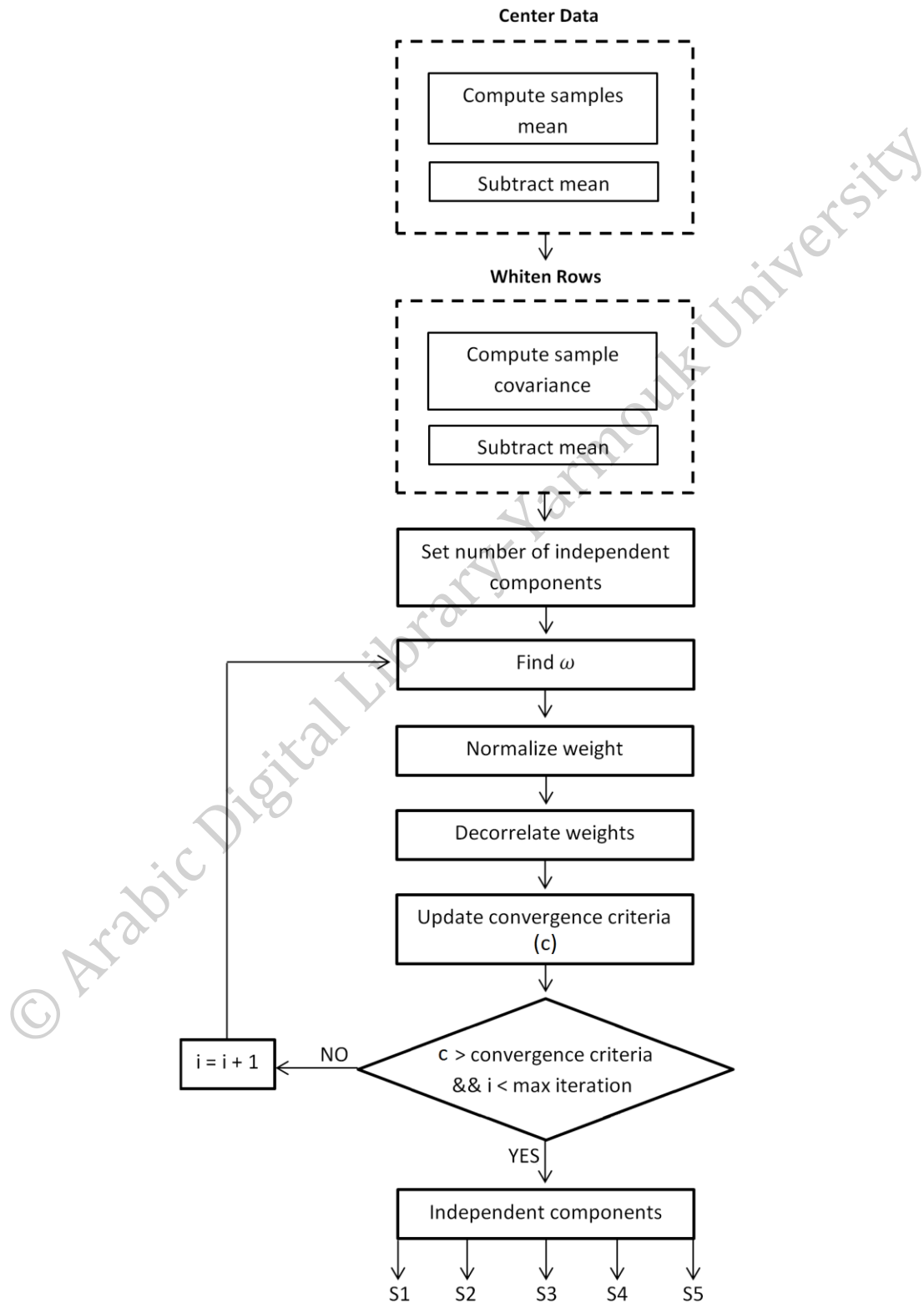


Figure 6: Main steps of FastICA algorithm.

3.1.3 Heart Rate Variability Construction

HRV is a signal to understand the Autonomic Nervous System (ANS) status and explains the variation in the period of time between two consecutive heartbeats, which reveals the non-consistent RR intervals. HRV analysis aims to assess the state and health of the ANS that is responsible for cardiac activity regulation (Acharya et al., 2006).

HRV signal describes the adaption of heart and its ability to respond to different types of changing. To construct HRV signal, the sequences of RR intervals are required to be resampled to obtain a regularly resampled signal because the HR is not constant with time. Therefore, RR intervals are changed with time, so the steady state process cannot be satisfied. Thus, estimation of RR intervals is required at specific points to make it satisfying the assumption of the steady state (Jang et al., 2012). An example of this process is illustrated in Figure 7. In this research, cubic spline interpolation will be applied in order to find the HRV signal from the FECG signal.

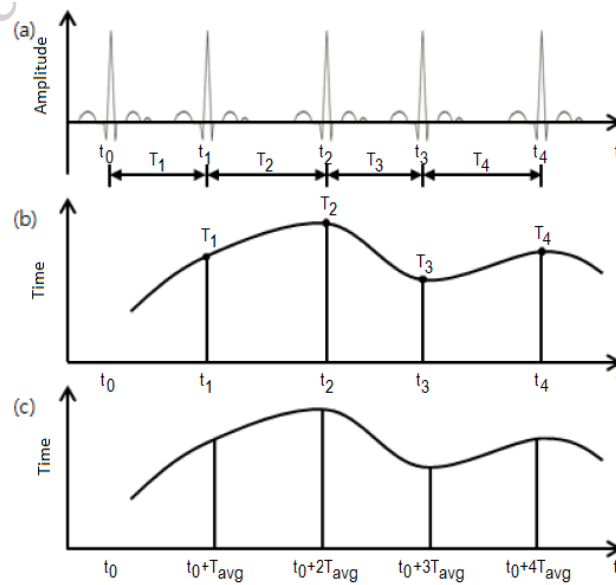


Figure 7: RR interval fitting example, (a) ECG signal (b) RR interval signal and (c) Resampling RR intervals (Jang et al., 2012).

The following steps are used to obtain a regularly resampled signal from RR intervals (Jang *et al.*, 2012):

Step 1: Calculate the average of all RR intervals to use it as a resampling period for resampled sequences of RR intervals evenly.

Step 2: An RR envelope signal is extracted using Cubic Spline Interpolation method.

Step 3: The RR envelope signal is resampled using the resampling period.

Step 4: The original RR intervals are replaced with the newly resampled signal.

Cubic spline interpolation will be used to construct the HRV signal from the signal of RR intervals. The cubic spline interpolation is a piecewise polynomial approximation that can be used for each two points in the N abscissae to approximate a curve between them. The cubic spline interpolation is given by Equation (4) (Jang *et al.*, 2012):

$$S_i(x) = \frac{Z_{i+1}}{6h_i} (x - x_i)^3 + \frac{Z_i}{6h_i} (x_{i+1} - x)^3 + \left(\frac{y_{i+1}}{h_i} - \frac{h_i}{6} Z_i\right) (x - x_i) + \left(\frac{y_i}{h_i} - \frac{h_i}{6} Z_i\right) (x_i - x) \quad (4)$$

Here, Z_i is given by Equation (5):

$$Z_1 = Z_n = 0$$

$$h_{i-1} Z_{i-1} + 2(h_{i-1} + h_i)Z_i + h_i Z_{i+1} = 6(C_i - C_{i-1}) \quad (5)$$

h_i and C_i is calculated by Equations (6) and (7) respectively:

$$h_i = x_{i+1} - x_i \quad (6)$$

$$C_i = \frac{y_{i+1} - y_i}{h_i} \quad (7)$$

Where x : number of samples.

x_i and y_i : coordinates of the current point.

x_{i+1} and y_{i+1} : coordinates of the next point.

h_i : the difference in x-coordinate between two consecutive points.

C_i : the ratio of the difference in y-coordinate to h_i .

Figure 8 represents the steps to construct HRV signals.

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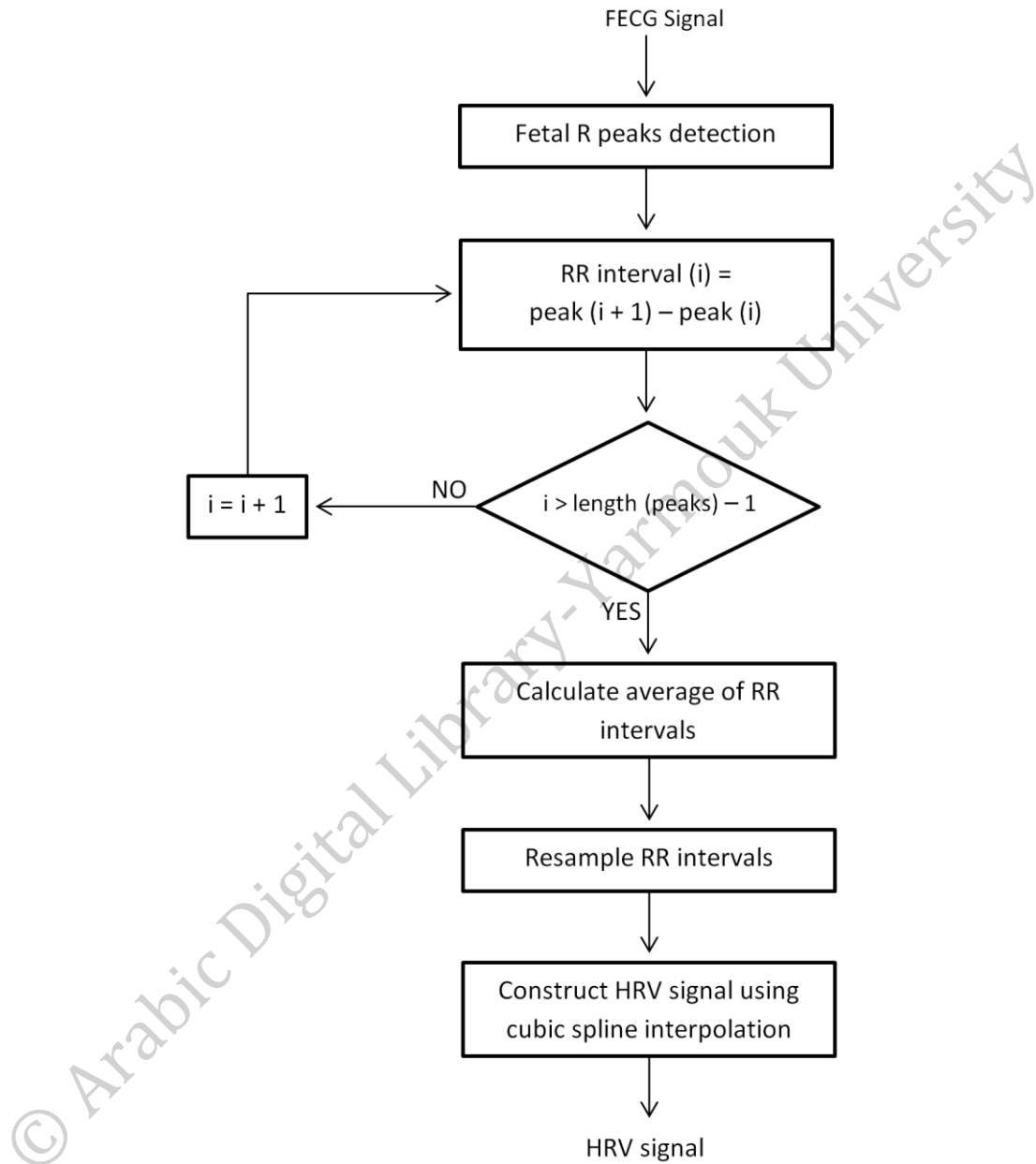


Figure 8: Steps of HRV signal construction, where FECG signal is the input signal. Then, the R peaks is detected, RR intervals calculation is done after that on the signal length. Finally, the signal is resampled using cubic spline interpolation.

3.1.4 Features Extraction

In this step, important information is extracted from the constructed HRV signal using DTCWT coefficients. Shift invariant and good directional selectivity properties of DTCWT make the transform useful in signal analysis application (Thomas, Das and Ari, 2014). The DTCWT consists of two trees (Tree A and Tree B) each one uses orthogonal set of filters. One gives the real part (Tree A) and the other gives the imaginary part (Tree B) of the wavelet coefficients. To achieve the shift invariance property, the sample rate is doubled in the tree by eliminating the down sampling by 2. (Selesnick, Baraniuk and Kingsbury, 2005). The basic steps for features extraction by using DTCWT coefficients are as follows:

Step 1: Decompose the HRV signal using 'cplxdt' (i.e. DTCWT) mother wavelet.

The decomposition produces DTCWT coefficients.

Step 2: Choose the DTCWT coefficients and calculate the absolute value for the real and imaginary coefficients.

Step 3: Calculate the features from the coefficients.

Step 4: Construct a features vector.

The decomposition using DTCWT technique corresponding to 2 levels is as shown in Figure 9.

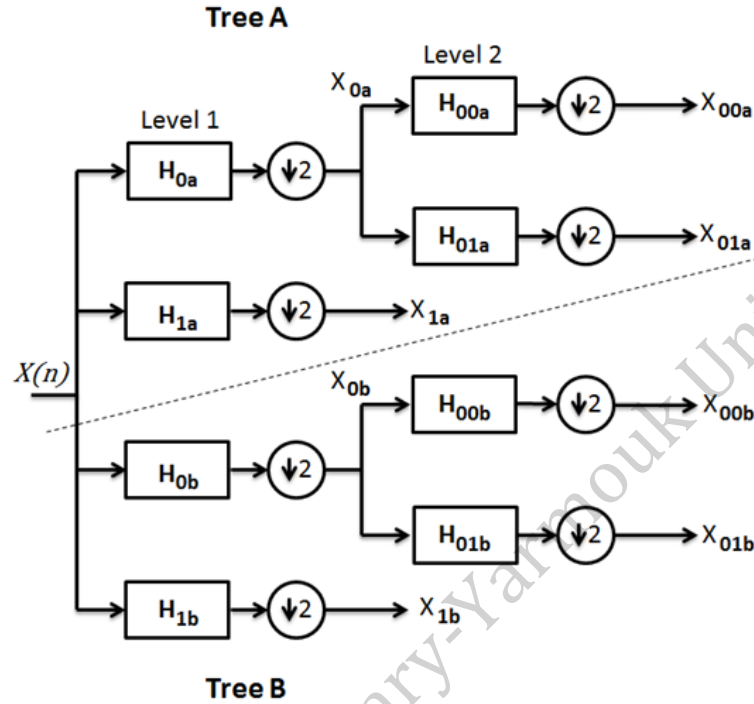


Figure 9: Two Levels Dual Tree Complex Wavelet Transform.

As shown in Figure 9, H_{0a} and H_{00a} are the low pass filters and H_{1a} and H_{01a} are the high pass filters for the Tree A. The same is true for the Tree B; H_{0b} and H_{00b} are the low pass filters and H_{1b} and H_{01b} are the high pass filters. X_{00a} , X_{1a} , X_{01a} , X_{00b} , X_{1b} and X_{01b} are the wavelet coefficients.

Feature extraction technique is about extracting significant information from the HRV signal. In this step, the extracted features represent the HRV signal in lower dimension. Therefore, the computational complexity is reduced and over fitting is decreased.

Using these features, a vector is constructed for each signal and is given as input to the SVM classifier. The features that are extracted from the coefficients of the HRV signal are:

1. **Mean:** The average of the sample, which is the center of the data (Bohm and Zech, 2010).

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (8)$$

2. **Standard Deviation:** Find how the spread out a set of observations is, which is equal to the square root of the variance (Bohm and Zech, 2010).

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (9)$$

3. **Maximum:** The largest value in the sample. Maximum used to determine if there is a mistake in the data entry.

$$\max = \max(\text{features vector}) \quad (10)$$

4. **Minimum:** The smallest value in the sample. Minimum used to determine if there is a mistake in the data entry.

$$\min = \min(\text{features vector}) \quad (11)$$

5. **Median:** Is the center of the data sample. It splits the sample; half the data are greater than the median and the other half are less than the median, but first the data sample must be sorted (Bohm and Zech, 2010).

$$median = \begin{cases} \frac{n+1}{2} & \text{odd numbers} \\ \frac{n}{2} & \text{even numbers} \end{cases} \quad (12)$$

6. Kurtosis: Measure the peaked or flat of the data, relative to a normal curve (Bohm and Zech, 2010).

$$kurtosis = \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{s} \right)^4 \quad (13)$$

7. Entropy: Used to express about the productivity or randomness of a system (Bohm and Zech, 2010).

$$entropy = - \sum_{i=1}^n p(x_i) \log p(x_i) \quad (14)$$

Where \bar{x} : the mean value.

n : represents number of data sample.

x_i : represents data.

s : the standard deviation.

$p(x_i)$: the probability function of x_i .

3.1.5 Classification

The features that are extracted from HRV signal in the previous step are classified in this step by using SVM classifier. SVM is a useful and powerful technique for classification in the biomedical field. The basic SVM takes data as a set of input and

separate data into two classes. To separate the data there are many hyperplanes (Figure 10 (a)), the best one will be the hyperplane with the maximum distance between the adjacent points in two classes (Figure 10 (b)), this distance is called Margin. Maximum margin property gives SVM advantage over other classifiers since the overlapping between the data in each class is insignificant.

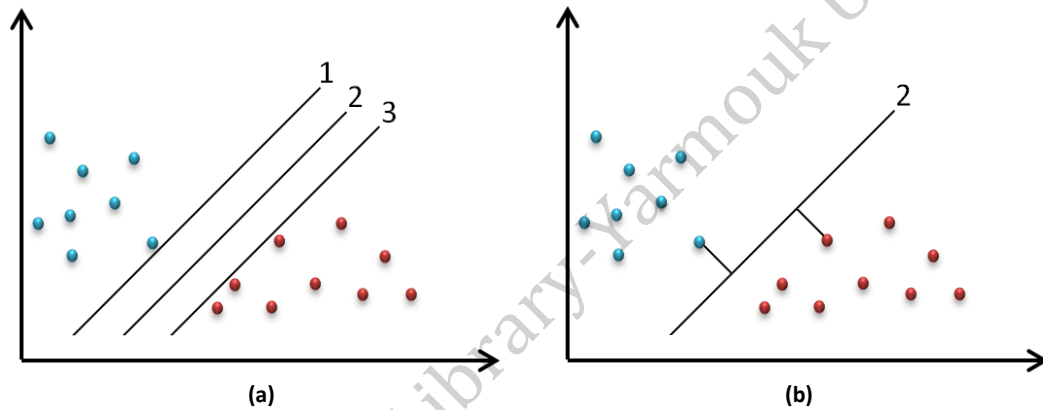


Figure 10: Works of support vector machine.

In this example, hyperplane 2 has the maximum margin compared to 1 and 3. The selection of the hyperplane that has higher margin makes robustness classification, while the selection of the hyperplane with lower margin increases the chance of misclassification. The steps for fetus heartbeats classification are as follow (Kalaiselvi *et al.*, 2016):

Step 1: Select the input data.

Step 2: Transfer input data into a higher dimensional feature space by calculating inner products of input data.

Step 3: Search for linear relations to separate hyperplane in the feature space with maximum margins for support vector.

Chapter 4

Implementation

The proposed method is implemented using MATLAB (Mathworks, 2014). The program provides suitable environment for signal processing, which provides several functions to generate, filter and analyze the signals. WEKA (Frank et al., 2016) is used for the classification purpose. This tool offers different classification methods. This work uses SVM, Naïve Bayes and J48 classification method from WEKA.

4.1 Signal Preprocessing

4.1.1 Removing noise

The abdominal signal preprocessing has two steps; noise suppression and baseline correction. Power line interference, instrumental noise and muscles contraction are some of noise source in the abdominal signal. Abdominal signals have noise frequency range of $0.01Hz - 100Hz$ (Sameni et al., 2007). Bandpass filter can be used for preprocessing step with a cutoff frequency between these ranges. This filter is fast and frequency based, also it is one of the digital filters that are used in signal analysis.

This research has used the following MATLAB built-in functions to design a bandpass filter:

```
1. bpf = fdesign.bandpass('N,F3dB1,F3dB2', n, c1, c2, fs);
```

The function has five parameters: the first one is to perform an IIR Butterworth filter with 3dB frequencies of the starting cutoff frequency (F3dB1) and ending cutoff frequency (F3dB2). The second parameter is the order for bandpass filter. While the third and fourth parameters are the range of cutoff frequency, which divides the signal frequency into pass band and stop band; pass band passes the frequencies that are in the range of cutoff frequency and stop band stops frequencies that are higher or less than the cutoff frequency. The final parameter is the sampling rate of the abdominal signal.

```
2. Hd = design(bpf, 'butter');
```

This function designs the filter with the properties from 1. After the filter is designed, the proposed method applies it on each abdominal signal. The pseudocode to filter the abdominal signal is illustrated in Algorithm 1.

Algorithm 1: Bandpass filter for abdominal signal

Input: abdominal signal (r_n).

Output: filtered abdominal signal.

$\forall r_n, n \in [1, 2, 3, 4]$

r: abdominal signal record.

n: number of input signals.

$r_fft \leftarrow \text{fft}(r_n, \text{length}(r_n)) / \text{length}(r_n)$

$r_frequency \leftarrow fs / 2 * \text{linspace}(0, 1, \text{length}(r_n) / 2 + 1)$

$r_amplitude = 2 * \text{abs}(r_fft(1 : \text{length}(r_n) / 2 + 1))$

Repeat $\forall r_n$

determine the cutoff frequency

$\text{bpf} \leftarrow \text{fdesign.bandpass}('N, F3dB1, F3dB2', 10, 0.5, 49, 1000)$

$Hd \leftarrow \text{design}(\text{bpf}, 'butter')$

$\forall r_n, n \in [1, 2, 3, 4]$

$\text{bpf_}r_n \leftarrow \text{filter}(Hd, r_n)$

Repeat $\forall r_n$

4.1.2 Removing Baseline Wander

Generally, baseline drift are caused by movement or respiration of the patient. To correct baseline wander, this research detrend the baseline drift and correct it by using `detrend` function. The function takes one parameter which is the abdominal signal and is called for every 0.5 second of the signal length to correct the baseline drift.

```
for i = 1 : 500 : length(ecg_r1)
    ecg1(i : i + 500 - 1) = detrend(ecg_r1(i : min(i + 500 - 1,
                                                length(ecg_r1))));
end
trend1 = ecg_r1 - ecg1;
```

4.2 FECG Signal Extraction

Since noise is attenuated and baseline drifts are removed FECG extraction can be started. The abdominal signal contains MECG signal and FECG signal. MECG signal is considered as a noise in FECG signal analysis with similar frequencies. So, in each abdominal record, we need a method to suppress the MECG signal and emphasize the FECG signal only.

To extract the FECG signal, the abdominal signal records are represented in one matrix (*number of records * records length*). Then this matrix is passed to `fastICA` function to extract the FECG signal as follow:

```
icasig = fastICA(ecg, ic);
```

This function takes two parameters; the first one is `ecg`, which is the matrix that contains all the records of abdominal signal. The second parameter is `ic`, which is the

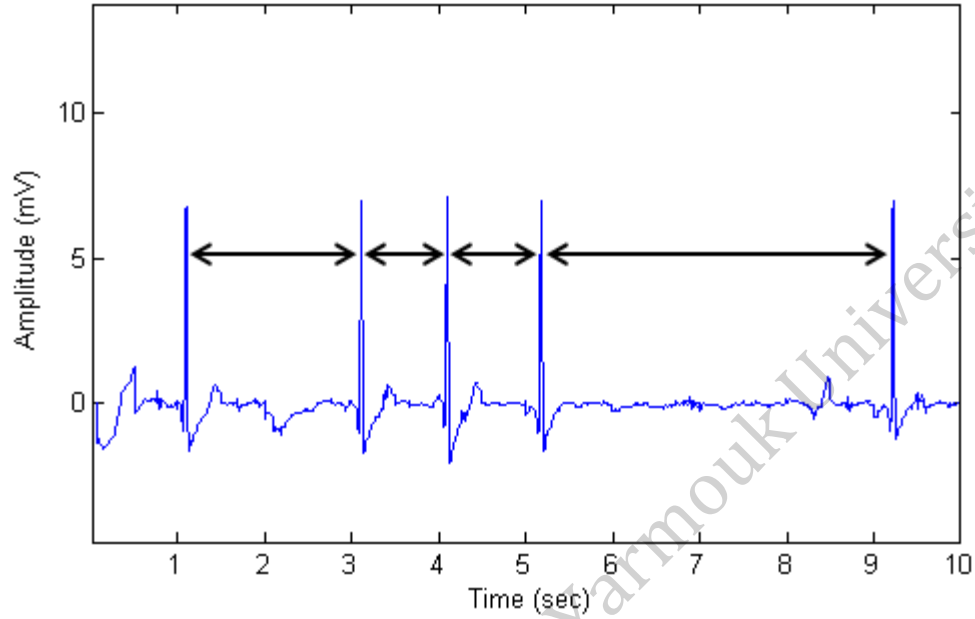


Figure 11: RR interval over cardiac cycles.

The proposed algorithm to construct the HRV signal is as follow:

- R peaks are detected based on minimum peak height and minimum peak distance.
- Then RR intervals are calculated based on the distance between every two consecutive R peaks. The process is repeated until all RR intervals are found.
- After that, the average of RR intervals is computed to use it as resampling period between RR intervals.
- The last step is to construct HRV signal using cubic spline interpolation method. The y-axis of the HRV signal represents the RR interval length.

Such analysis offers statistical information to assess fetus cardiac health. Algorithm

3 represents the procedure to construct HRV signal.

Algorithm 3: HRV Construction Algorithm

Input: FECG signal.

Output: HRV signal.

$RL \leftarrow \text{findpeaks}(\text{fecg})$

RL: location of each R peak

$T \leftarrow 0$

T: summation of distances
of all RR intervals

$\forall RL_n, n \in [1, 2, \dots, \text{length}(RL) - 1]$

$RR_n \leftarrow RL_{n+1} - RL_n$

RR: RR intervals

$T \leftarrow T + RR_n$

Repeat $\forall RL_n$

$T_{\text{avg}} \leftarrow T / \text{length}(NRL)$

$\text{samp} \leftarrow \text{length}(NRL)$

$x \leftarrow 1 : T_{\text{avg}} : \text{samp} * T_{\text{avg}}$

$xx \leftarrow \text{linspace}(1, \text{samp} * T_{\text{avg}} - T_{\text{avg}}, \text{samp} \wedge 3)$

$\text{hrv} \leftarrow \text{spline}(x, NRL, xx)$

The result of this algorithm is presented in Figure 12. This Figure is the constructed HRV signal from FECG signal in Figure 11.

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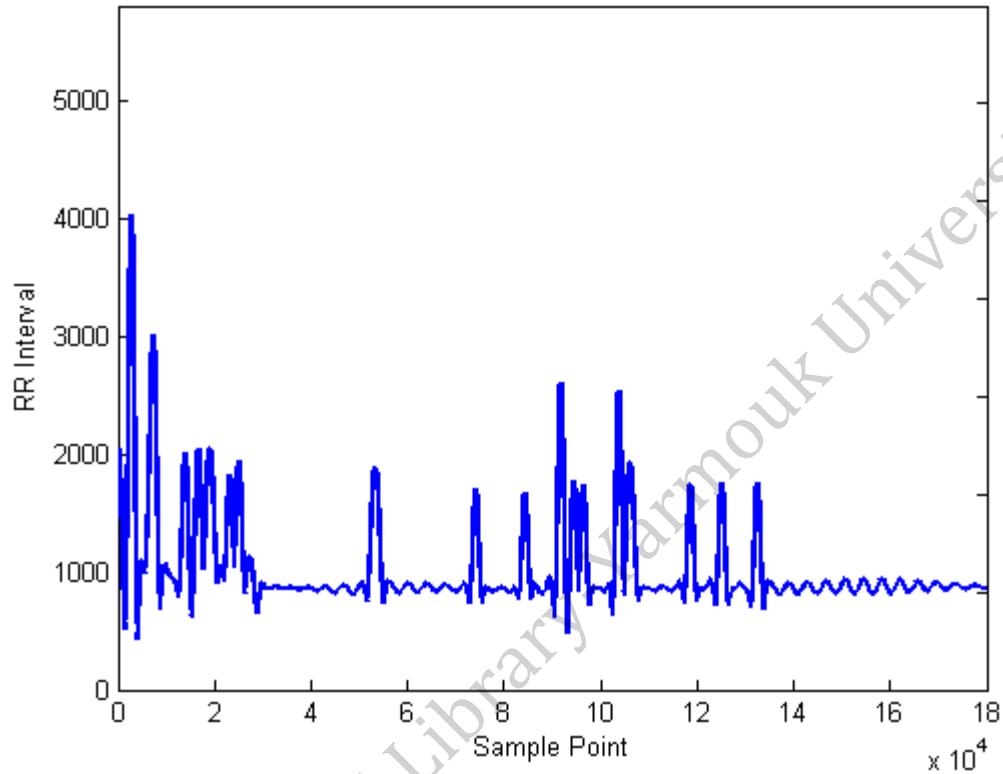


Figure 12: Constructed HRV signal using Algorithm 3.

4.4 Features Extraction

Features are computed by decomposing the HRV signal using DTCWT. The transform results in a set of coefficients. Mean, standard deviation, maximum, minimum, median, kurtosis and entropy of the coefficients are calculated according to equations (8), (9), (10), (11), (12), (13) and (14) respectively. The main goal of this step is to reduce the dimensionality of DTCWT transformation. The decomposition is done using `dddtree` function:

```
dt = dddtree('cplxdt', hrv, L, DF{1}, DF{2});
```

This function takes five parameters:

- The first parameter is the wavelet decomposition type; 'cplxdt', which is the dual tree complex wavelet transform.
- The second parameter is the HRV signal, this signal must be even-length row vector or column vector.
- L is the third parameter, which is the wavelet decomposition level.
- The fourth and fifth parameters $DF\{1\}$ and $DF\{2\}$ are the analysis filter for level one and the rest of level respectively.

The extracted features construct a feature vector then can be used to classify the record. Feature extraction process is illustrated in Algorithm 4.

Algorithm 4: Feature Extraction Process.

Input: HRV signal.

Output: features vector.

```
DF ← dtfilters('dtf1')
```

```
L ← 1
```

L: decomposition level.

```
dt ← dddtree('cplxdt', hrv, L, DF{1}, DF{2})
```

```
CFS ← abs(dt.cfs{L}(:, :, 1))
```

```
M ← mean(CFS)
```

```
STD ← std(CFS)
```

```
MAX ← max(CFS)
```

```
MIN ← min(CFS)
```

```
MED ← median(CFS)
```

```
KUR ← kurtosis(CFS)
```

```
ENT ← entropy(CFS)
```

```
feature ← [M STD MAX MIN MED KUR ENT]
```

4.5 Classification

The feature vector from each case is saved in a matrix. The last column is the state of the abdominal signal (normal or abnormal). To classify the state of abdominal signal, this research uses WEKA. Features matrix is used as an input for SVM classifier then Normalize filter is applied on the matrix.

This research uses LibSVM two parameters; cost and gamma. Cost parameter try to avoid misclassification for each training point. High values of cost selects small margin, which causes better results in the classification, while low values of cost selects large margin. Gamma parameter defines the influence of a single training example; if gamma has low value that means every point has a far reach and conversely high values means that every training example has a close reach. In other words, with high values of gamma, close points are considered in hyperplane calculation. While low values of gamma, far points are considered to find the hyperplane that separates the normal and abnormal cases.

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Chapter 5

Experimental Results

This chapter presents the results of the proposed method according to signals from 105 pregnant women. The accuracy, sensitivity and specificity of the proposed method are found for 1, 3, 5 and 15 minutes signal length. The following sections provide more details about dataset and the results of the proposed method.

5.1 Dataset

Since there are no datasets publicly available for abdominal ECG signals for pregnant women, we built our own dataset using FECGSYN tool. The tool can generate abdominal signals that have the same pathological characteristics of a real signal (Andreotti *et al.*, 2016). It can also convolute noise and respiration artifacts with the abdominal signal.

As a validating step for using this tool, a total of 105 abdominal signals were generated and evaluated by an expert. Each abdominal signal is comprised of 15 minutes obtained from 32 channels. Since FastICA method requires a number of observations equal to or greater than the number of the independent components, the number of available information is reduced to only 4 abdominal channels according to MIT-BIH physionet specifications (AL *et al.*, 2000).

The volume conductor for the 34 channels (32 abdominal channels and 2 thoracic channels) is represented in Figure 13.

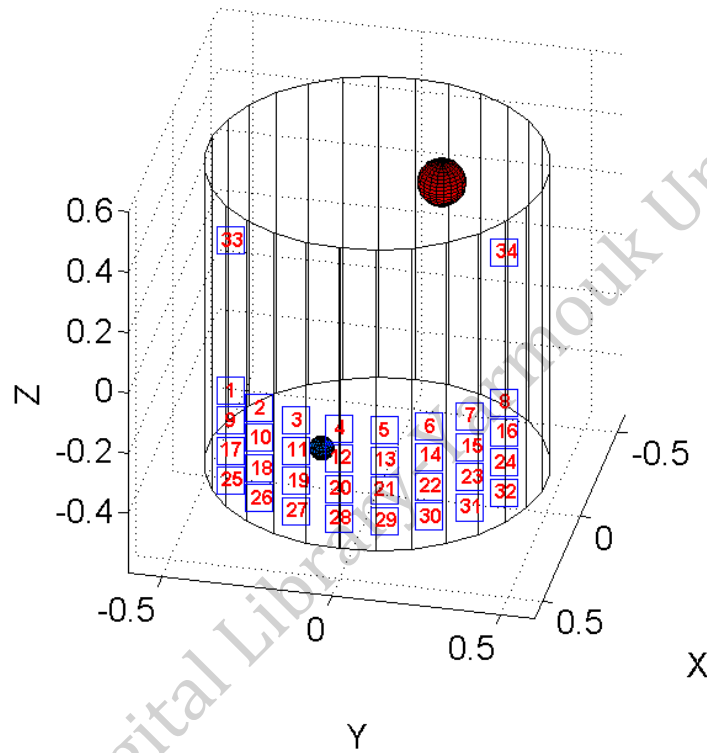


Figure 13: View of the volume conductor.

The above figure represents the abdomen of a pregnant woman. There are 34 channels, 2 thoracic channels (33 and 34) and 32 abdominal channels (1 – 32). Each signal have 4 abdominal channels, which are selected randomly. Small sphere represent the position of fetus heart and large sphere the maternal heart position.

The parameters used through for building this dataset are listed in Table 3. These parameters generate abdominal signals with different clinical diagnostics (as ensured by an expert).

Table 3: Used key parameters to simulate the mixture of fetus and maternal signals.

Parameter	Values	Unit
Fetus heart rate	[60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200]	bpm
Maternal heart rate	[70, 75, 80, 85, 90, 95, 100]	bpm
Fetus maternal SNR	[-10, -1, 5]	dB
Maternal SNR	[1, 5, 9, 40]	dB
Frequency	1000	Hz

5.2 Performance Measure

The performance of the proposed method is evaluated based on sensitivity, specificity and accuracy. The terms that are used to describe sensitivity, specificity and accuracy are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Positive terms indicate that the fetus is unhealthy, while negative terms indicate that the fetus is healthy:

- **True Positive (TP):** Means that the fetus is unhealthy and the diagnostic test indicates that the fetus is unhealthy too.
- **True Negative (TN):** Means that the fetus is healthy and the diagnostic test indicates the fetus is healthy.
- **False Positive (FP):** Means that the fetus is healthy, but the diagnostic test indicates that the fetus is unhealthy.
- **False Negative (FN):** Means that the fetus is unhealthy, but the diagnostic test indicates that the fetus is healthy.

The confusion matrix is a methodology used to display the classification results in a tabular form. The rows of this matrix are the true classification and the columns are the predicted classification. The best situation for the confusion matrix to be the predicted classification is the same as the desired classification. Table 4 illustrated the formation of this matrix.

Table 4: The contents of the confusion matrix.

		Predicted Condition	
		Predicted Condition Positive	Predicted Condition Negative
True Condition	Total Population		
	Condition Positive	TP	FN
	Condition Negative	FP	TN

TP, TN, FP and FN are the description of accuracy, sensitivity and specificity, which can be calculated as in Equations (15), (16) and (17) respectively. Accuracy is the percentage of the system to identify correct cases, sensitivity is the percentage of the system to identify unhealthy cases and specificity is the percentage of the system to identify healthy cases (Zhu, Zeng and Wang, 2010).

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (15)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (16)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (17)$$

5.3 Experiments

5.3.1 Experiment 1: Different Classification Methods

SVM, J48 and Naïve Bayes classifiers have been used and the results of each classifier are compared with the others to find out which classifier is suitable for this research. WEKA is used in order to perform the classification. The features of all normal and abnormal cases are normalized before classification.

5.3.2 Experiment 2: Variable Signal Length

In this research, different signal lengths are used and tested in the proposed method to find out if the signal length affects the detection of normal and abnormal FECG signals. The incorporated lengths are 1, 3, 5 and 15 minutes long.

5.3.3 Experiment 3: Different Testing Options

5.3.3.1 10-Folds Cross-Validation

In this process, the instances are randomly divided into 10 sets. Each set is of size $n/10$, where n is the number of instances. One set is selected as a testing set and the other 9

sets are used for training. The process repeated 10 times and finally the average is calculated. The advantage of Cross-Validation method is that all signals are used for both testing and training.

5.3.3.2 Leave-One-Out Cross Validation

Leave-One-Out Cross-Validation method is also used to classify the signals. This method selects one signal from the samples at each step and uses it as a testing signal while the other signals are used as training. The process is repeated until each signal is selected as a testing signal. The advantage of this method is it close to the real-life application; takes one abdominal signal and test if the fetus is healthy or not.

5.4 Results

This section presents the experimental results for the proposed method, as well as parameters settings.

5.4.1 Signal Preprocessing

As mentioned in chapter three, the first step in the method is to attenuate noise and baseline drift in the signal. Such artifacts are reduced by applying a bandpass filter on the acquired signal. By using a bandpass filter, noise can be attenuated to an acceptable percentage. However, baseline drift removal still needs additional processing. There are some parameters that have an effect on the bandpass filter performance. Table 5 shows

these parameters and their selected values: the type of filter, the order of the bandpass filter, the cutoff frequency and the sampling rate of the abdominal signal.

Table 5: Key parameters of the bandpass filter.

Parameter	Definition	Value
'N,F3dB1,F3dB2'	IIR Butterworth filter	'N,F3dB1,F3dB2'
n	Order of the bandpass filter	10
c1	Low frequency of the cutoff frequency	0.5
c2	High frequency of the cutoff frequency	49
fs	Sampling rate of the abdominal signal	1000

The bandpass filter is designed with filter order equal to 10, because if the value is increased more than 10 the transition from the pass band to the stop band become steeper. The values of cutoff frequency are selected based on FFT as shown in Figure 14. Finally the value of frequency is selected to cover all the frequencies of the devices that are available in the hospitals.

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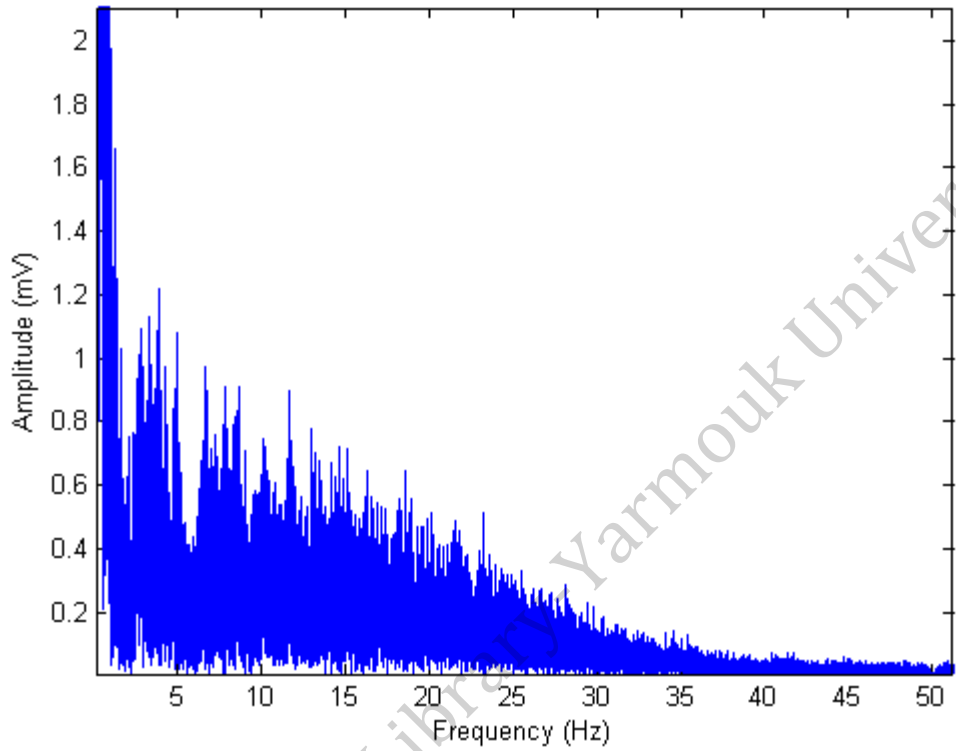
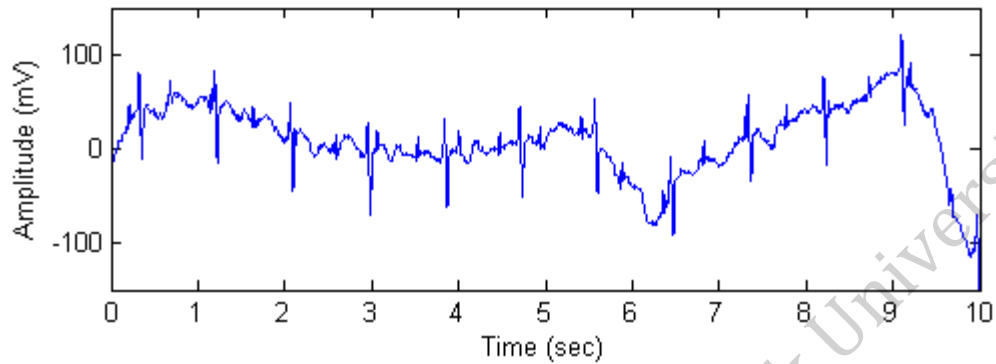
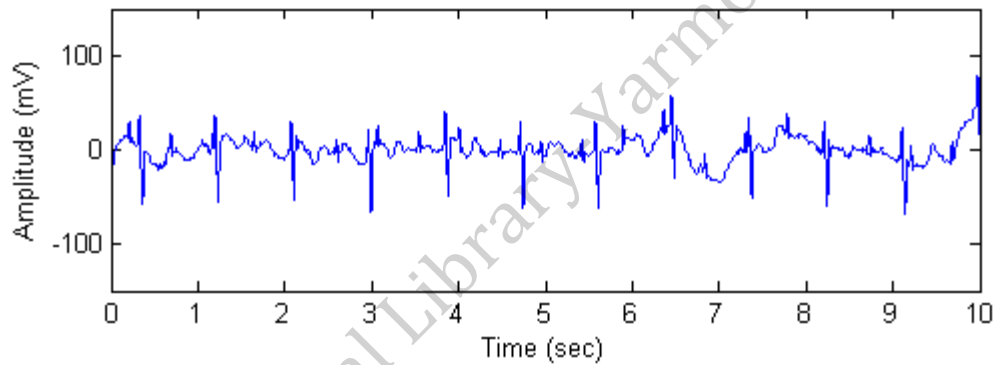


Figure 14: Power spectrum of abdominal signal by FFT.

Figure 15 below shows a 10 seconds of an abdominal signal before and after applying the bandpass filter. The noise exists in the abdominal signal cannot be removed completely (Simegn, Kassaw and Addis, 2015). However, suitable values for bandpass filter parameters can help to get a cleaner signal.



(a)



(b)

Figure 15: (a) Abdominal ECG signal and (b) The filtered signal using bandpass filter.

The above figure illustrates the results that are obtained by applying a bandpass filter with the listed parameters in Table 5. As the figure is shows, the filter does not remove the baseline drifts completely from the signal. As a result more computation is required to decrease its effect. Baseline drift removal is discussed in chapter three.

Figure 16 shows 10 seconds of the abdominal signals after correct the baseline drift. The detrending is performed on the signal every 0.5 seconds.

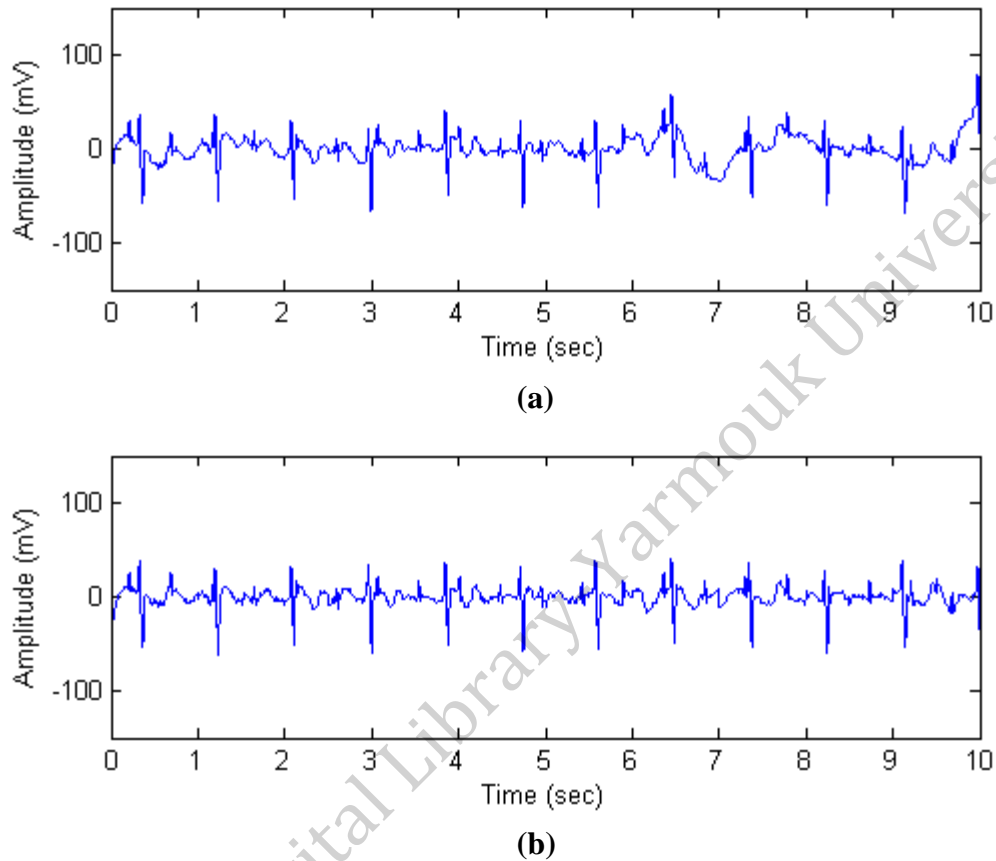


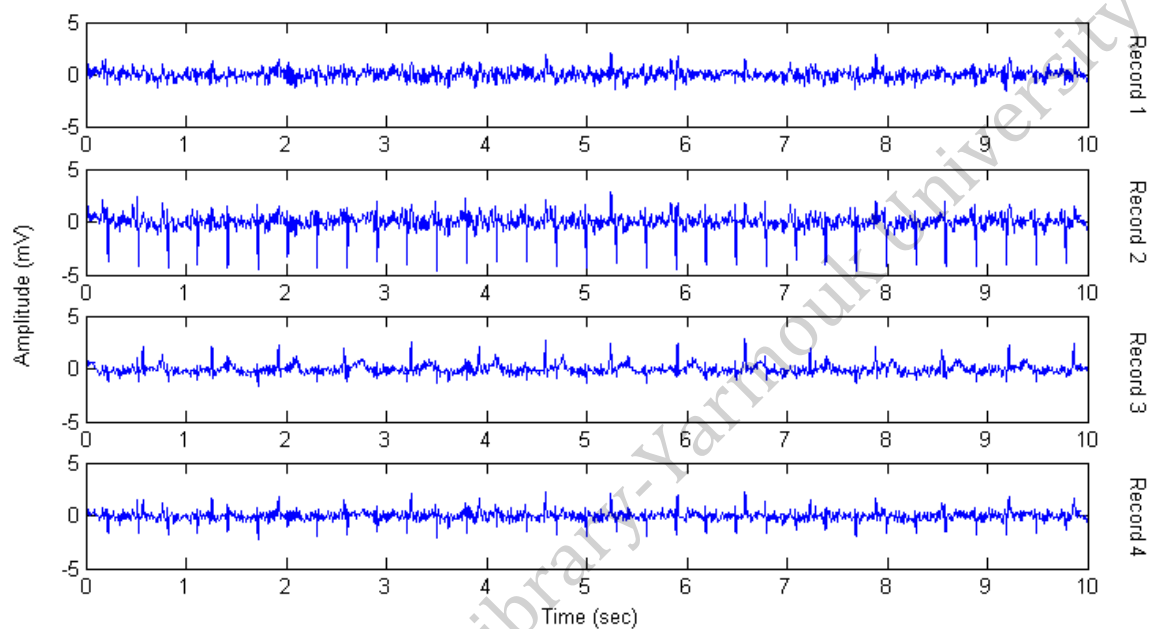
Figure 16: Abdominal signals (a) baseline drift and (b) corrected baseline.

As shown in the figure, baseline drift in abdominal signal makes the amplitude harder to read at a specific time. Therefore, it is important to correct the baseline drift.

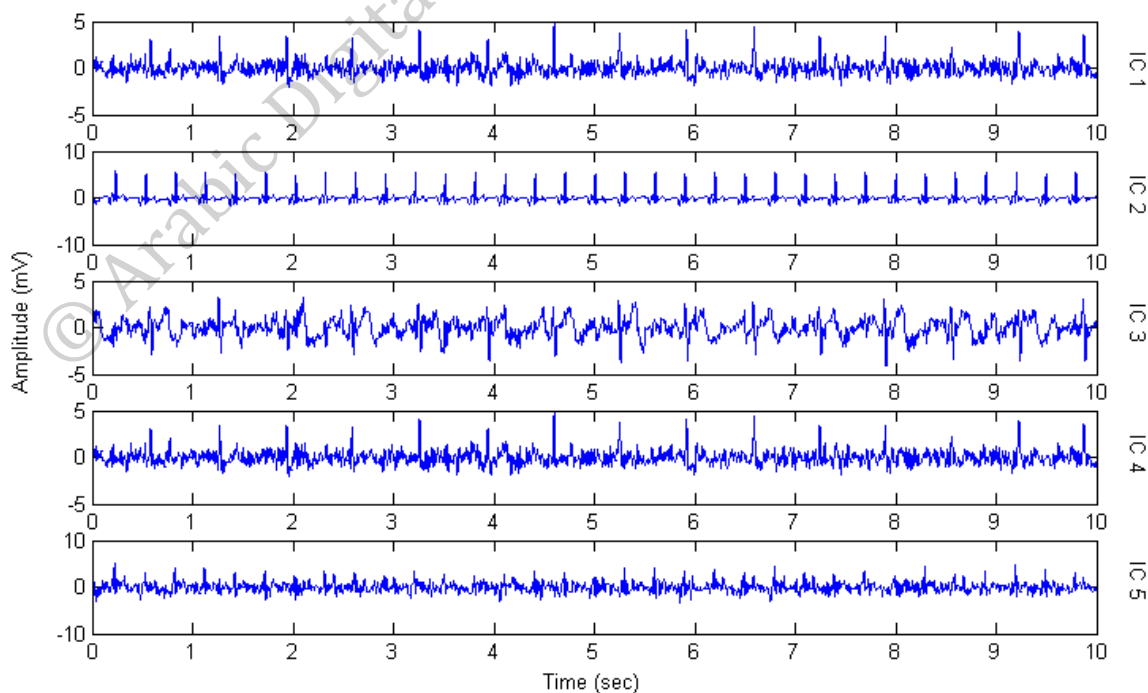
5.4.2 FECG Signal Extraction

In this research, FastICA is used to separate MECG from FECG signal in the abdominal signal. The method takes a matrix of abdominal records, where each row corresponds to an individual record and the columns to the samples of this record. Results of FastICA are summarized in Figure 17. The signals in (a) are the four input records to the

method. In (b) the independent components from the output of FastICA method are illustrated.



(a): Input abdominal signal records to FastICA method.



(b): Output signals of the FastICA method.

Figure 17: FECG signal extraction.

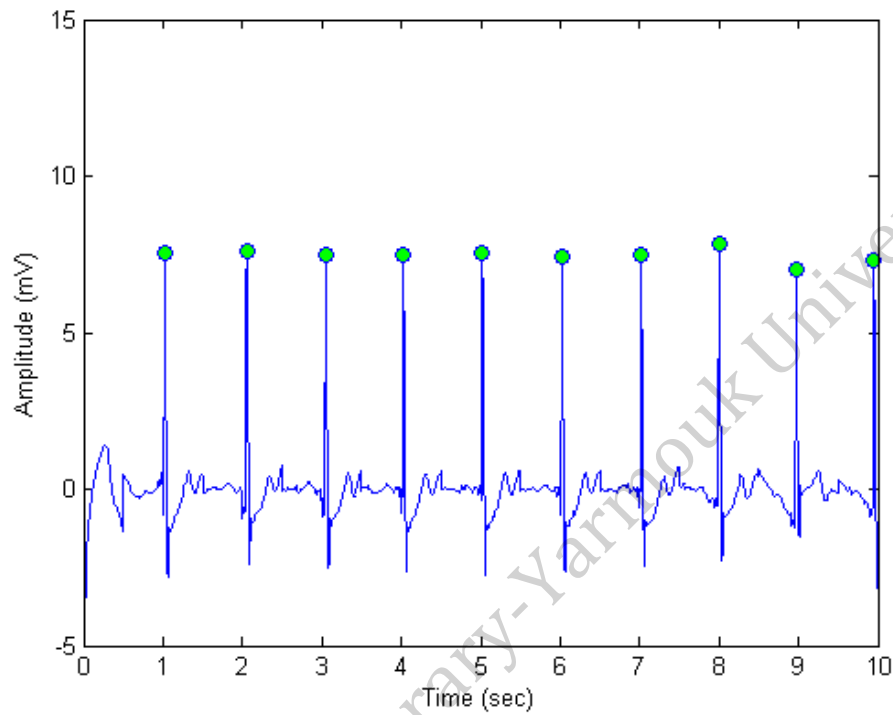
As can be seen from the figure, FECG signal can be extracted from the abdominal signal using FastICA. To select the FECG signal from the independent component, the signal with maximum amplitude is select, which corresponds to the FECG signal.

5.4.3 HRV Signal Construction

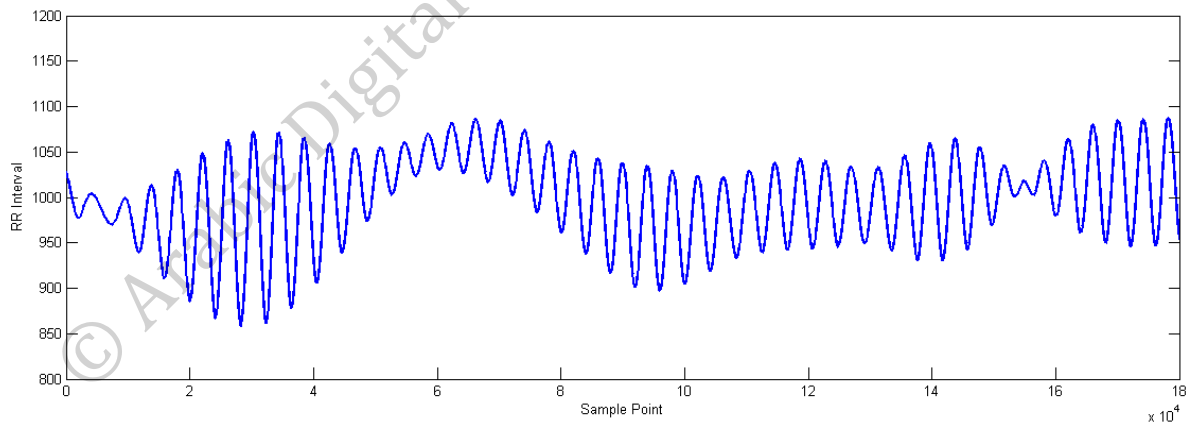
To construct HRV signal, the first step is to detect FECG peaks, which is detected based on the relative amplitude of the R peaks and the adjacent samples. Then the RR intervals of the signal are calculated based on the difference between each two consecutive R peaks. Finally HRV signal is constructed by applying Cubic Spline Interpolation method. The method is used to approximate the curve between each RR intervals.

Figure 18, 19 and 20 illustrate the results of R peaks detection for three different cases; normal, abnormal (Bradycardia) and abnormal (Tachycardia) in (a) and (b) the results of the interpolation.

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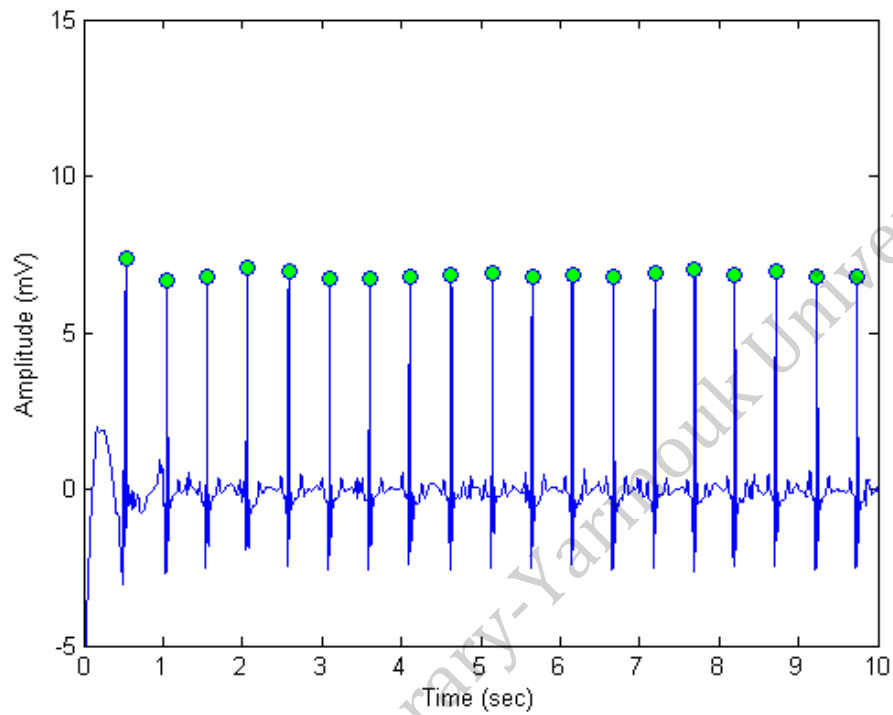


(a): R peaks detection from FECG signal.

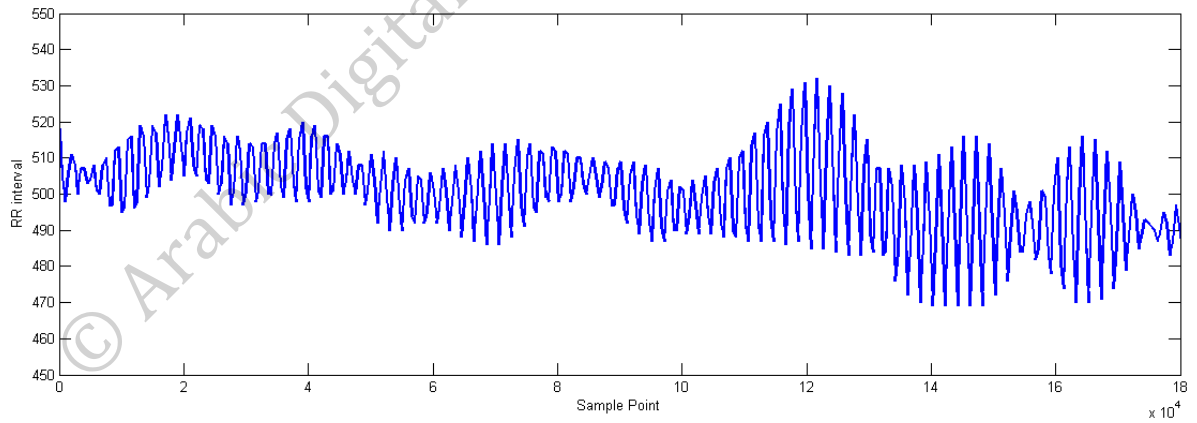


(b): The interpolated HRV signal.

Figure 18: R peaks detection from abnormal FECG signal (Bradycardia) and the constructed HRV signal from it.

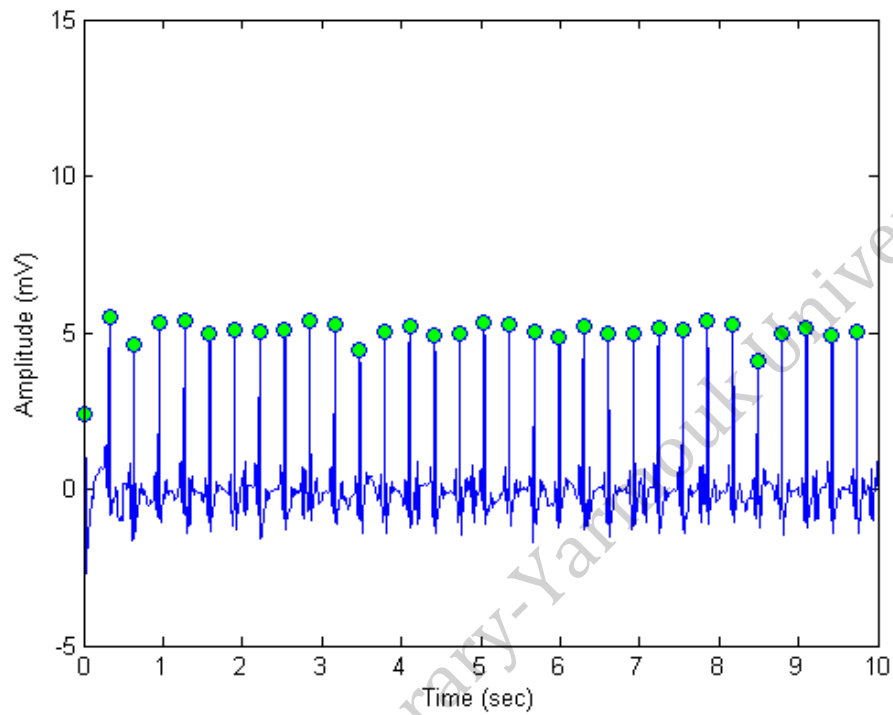


(a): R peaks detection from the FECG signal.

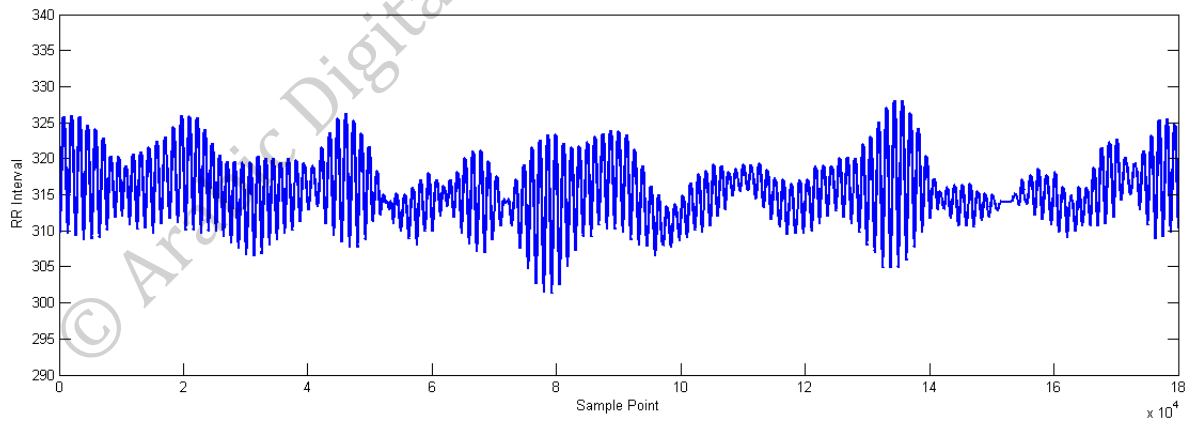


(b): The interpolated HRV signal.

Figure 19: R peaks detection from normal FECG signal and the constructed HRV signal from it.



(a): R peaks detection from the FECG signal.

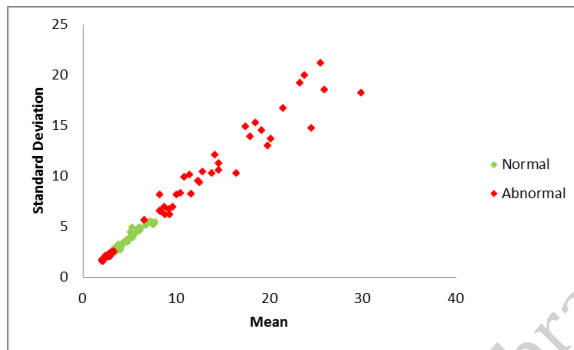


(b): The interpolated HRV signal.

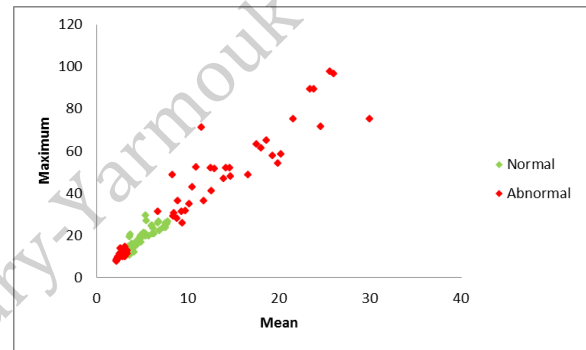
Figure 20: R peaks detection from abnormal FECG signal (Tachycardia) and the constructed HRV signal from it.

5.4.4 Features Extraction

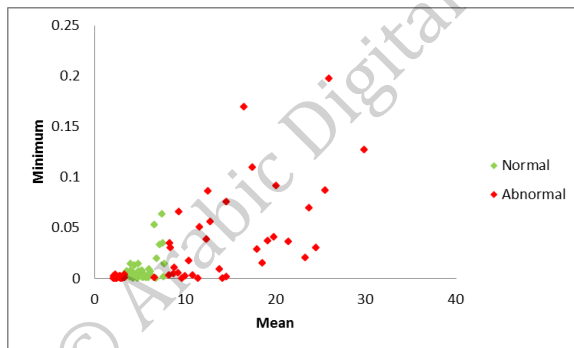
After constructing the HRV signal, the signal is then decomposed by DTCWT. From the resulted coefficients, seven features are calculated including mean, standard deviation, maximum, minimum, median, entropy and kurtosis. Spatial scattering of the relationship between each two of these features is presented in Figure 21 (a) to (u).



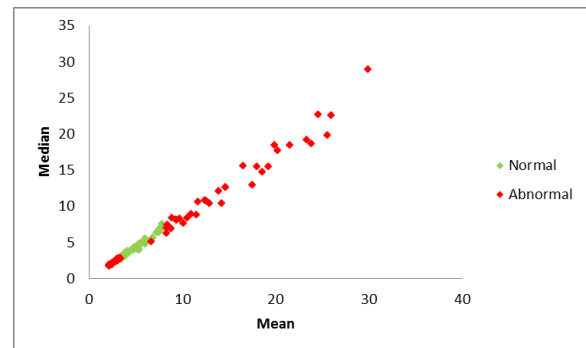
(a): Mean and standard deviation



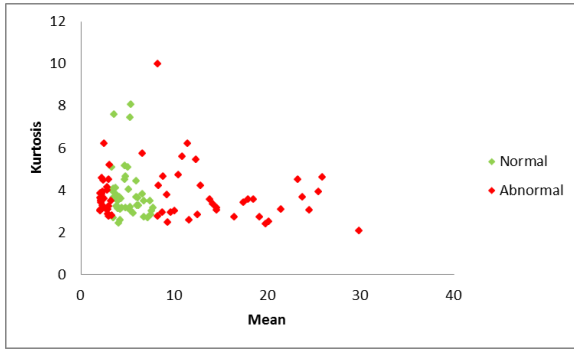
(b): Mean and maximum



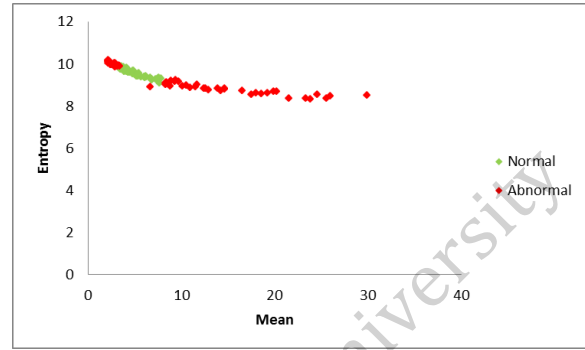
(c): Mean and minimum



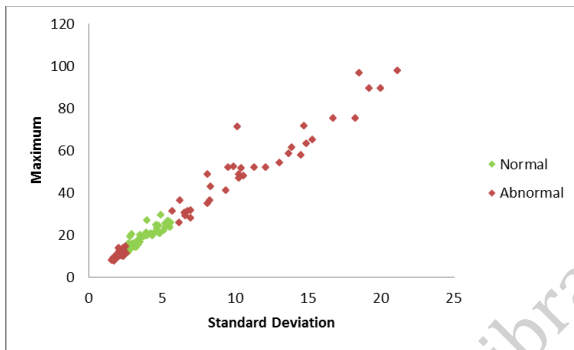
(d): Mean and meadian



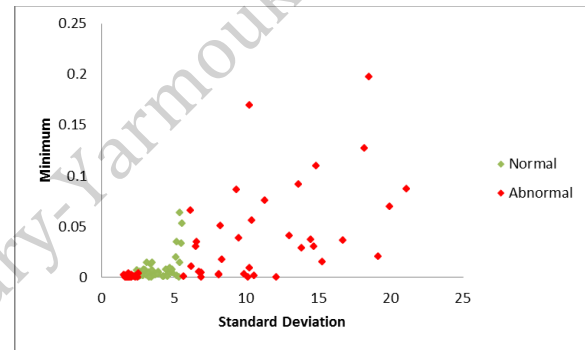
(e): Mean and kurtosis



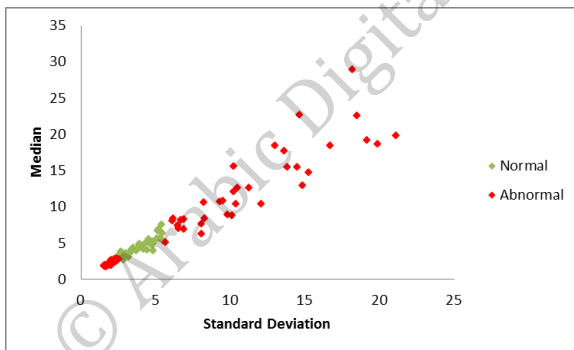
(f): Mean and entropy



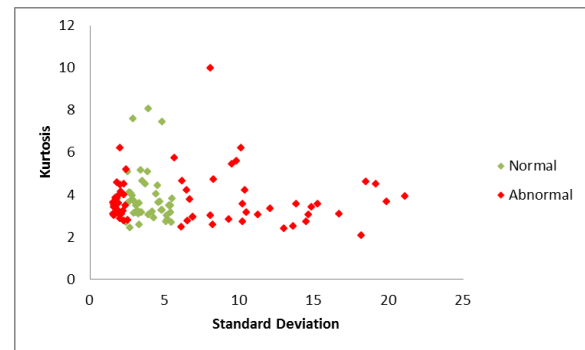
(g): Standard deviation and maximum



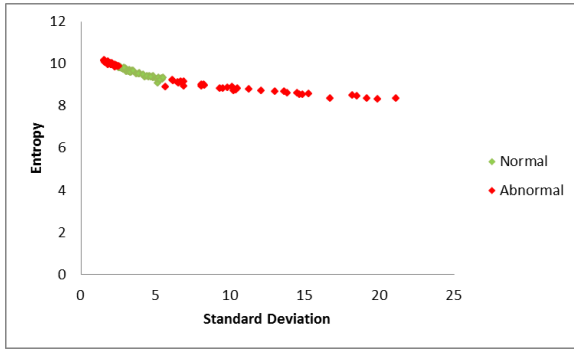
(h): Standard deviation and minimum



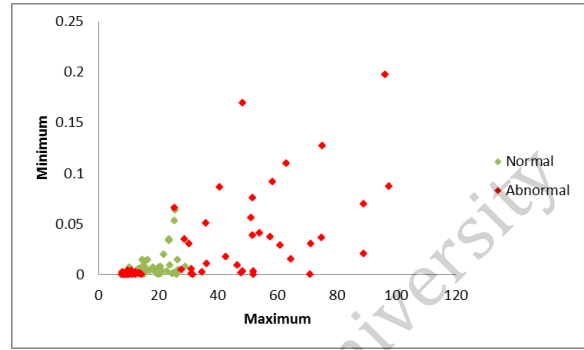
(i): Standard deviation and median



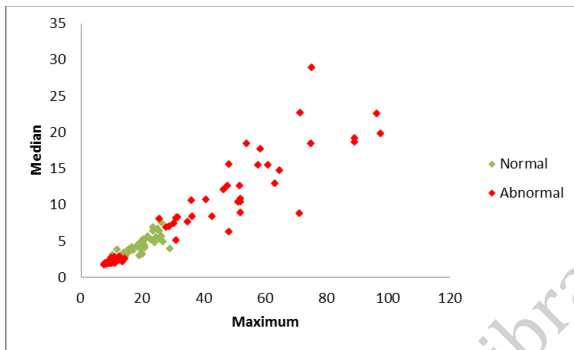
(j): Standard deviation and kurtosis



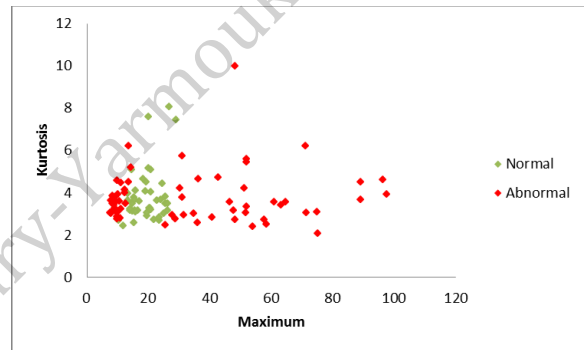
(k): Standard deviation and entropy



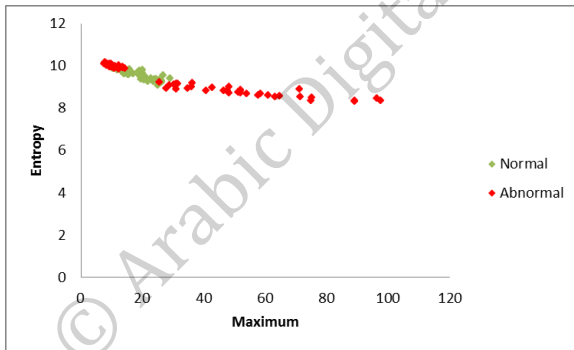
(l): Maximum and minimum



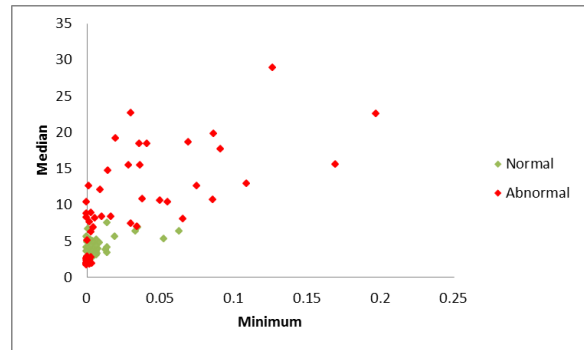
(m): Maximum and median



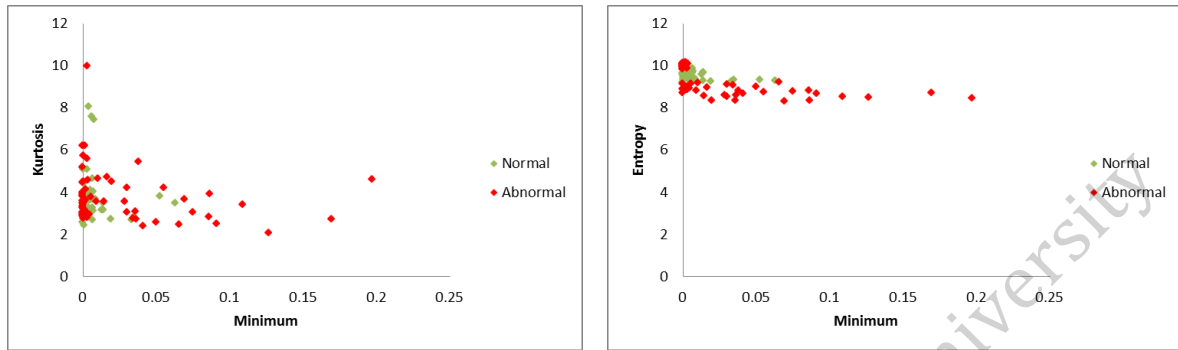
(n): Maximum and kurtosis



(o): Maximum and entropy

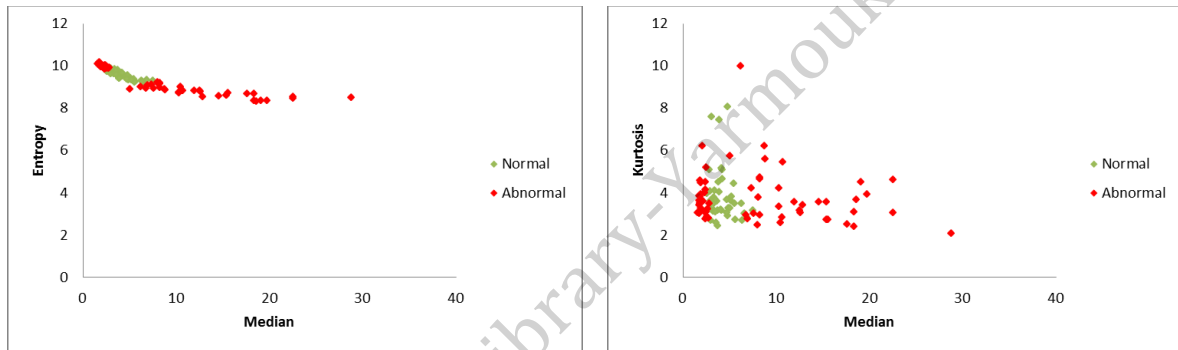


(p): Minimum and median



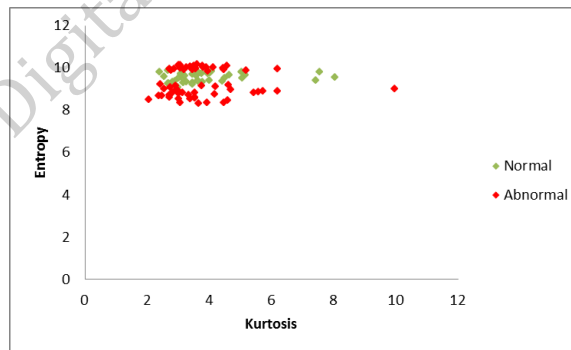
(q): Minimum and kurtosis

(r): Minimum and entropy



(s): Median and entropy

(t): Median and kurtosis



(u): Kurtosis and entropy

Figure 21: Spatial distribution of the extracted features.

Then the extracted features from the DTCWT coefficients are used to construct the features matrix. The rows of the matrix represent features vector of each signal, and each column is one of the features. This matrix is passed to the classification phase to find the results of the proposed method.

5.4.5 Classification

To distinguish between normal and abnormal FECG signals, SVM, J48 and Naïve Bayes classifiers are used. The result of each classifier is compared with the others to find out which classifier is better. WEKA is used in order to do the classification process. The features of all normal and abnormal cases are normalized and classified using 10-Folds Cross-Validation testing option. Table 6 shows the confusion matrix of SVM, J48 and Naïve Bayes classifiers when the whole signal (15 minutes) is classified.

Table 6: Confusion matrix of SVM, J48 and Naïve Bayes with 15 minutes signals.

N = 105	Abnormal	Normal	
Abnormal	62	1	SVM
Normal	2	40	
Abnormal	60	3	J48
Normal	2	40	
Abnormal	47	16	Naïve Bayes
Normal	5	37	

The confusion matrix in Table 6 shows the ratio of correct classification and miss-classification for normal and abnormal cases. As shown in the table SVM has the best results, which can detect 40 out of 42 of normal cases, while 62 out of 63 of abnormal cases. Accuracy not only differs from one classifier to other but on the different cases as

well (normal and abnormal). For example, abnormal cases are perfectly obtained for SVM classifier, while it caused in high error rate for Naïve Bayes classifier.

The ability of the proposed method to detect if the fetus cardiac is healthy or not is evaluated by using accuracy, sensitivity and specificity measures according to Equations (15), (16) and (17) respectively. The method is tested for 5, 3 and 1 minute to find if it is possible to detect normal and abnormal cases in shorter time. Table 7, 8 and 9 report the obtained results of these intervals.

Table 7: Accuracy, sensitivity and specificity for the intervals using SVM classifier.

Signal Length	Accuracy	Sensitivity	Specificity
15 min	97.14%	98.41%	95.23%
5 min	98.41%	98.41%	98.41%
3 min	96.38%	95.71%	96.82%
1 min	94.22%	92.85%	95.13%

Table 8: Accuracy, sensitivity and specificity for the intervals using J48 classifier.

Signal Length	Accuracy	Sensitivity	Specificity
15 min	95.23%	95.23%	95.23%
5 min	95.55%	94.44%	96.29%
3 min	91.8%	90.47%	92.69%
1 min	92.25%	89.04%	94.39%

Table 9: Accuracy, sensitivity and specificity for the intervals using Naïve Bayes classifier.

Signal Length	Accuracy	Sensitivity	Specificity
15 min	80%	74.6%	88.09%
5 min	68.88%	95.23%	51.32%
3 min	68.19%	94.76%	50.47%
1 min	65.58%	94.12%	46.56%

The previous tables show that the accuracy, sensitivity and specificity differ with the signal length for all classifiers. SVM and J48 classifiers achieved the best results when the signal length is 5 minutes. In this case sensitivity percentage is rises, which means medical errors (abnormal cases classified as normal cases) in this length are reduced than when the whole signal is analyzed. But they are actually in increasing as shown in Table 10, since 2 abnormal fetuses are classified as normal.

Table 10: Confusion matrix of the SVM for 5 minutes signal length.

N = 315	Abnormal	Normal
Abnormal	124	2
Normal	3	186

The confusion matrix shows that the number of abnormal cases that are detected as normal by the proposed method is 2, compared to 1 when the whole signal is analyzed. Therefore, the proposed method provides better results when 15 minutes long signals are used. Figure 22, Figure 23 and Figure 24 represent comparisons between different signal

lengths for accuracy, sensitivity and specificity by using SVM, J48 and Naïve Bayes classifiers.

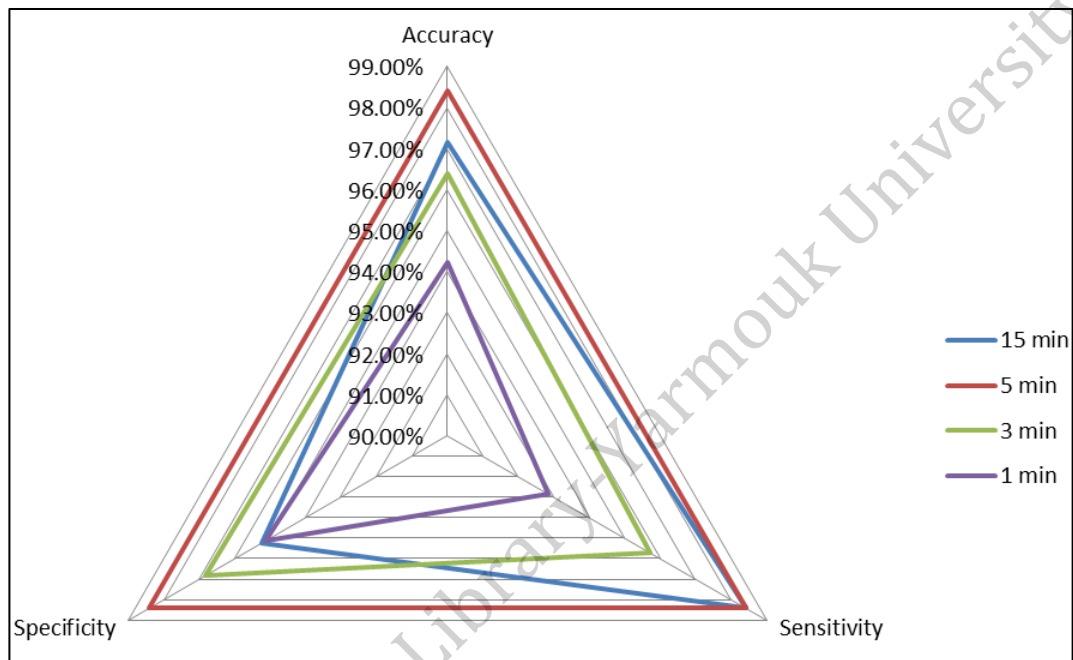


Figure 22: Ratio of accuracy, sensitivity and specificity using SVM.

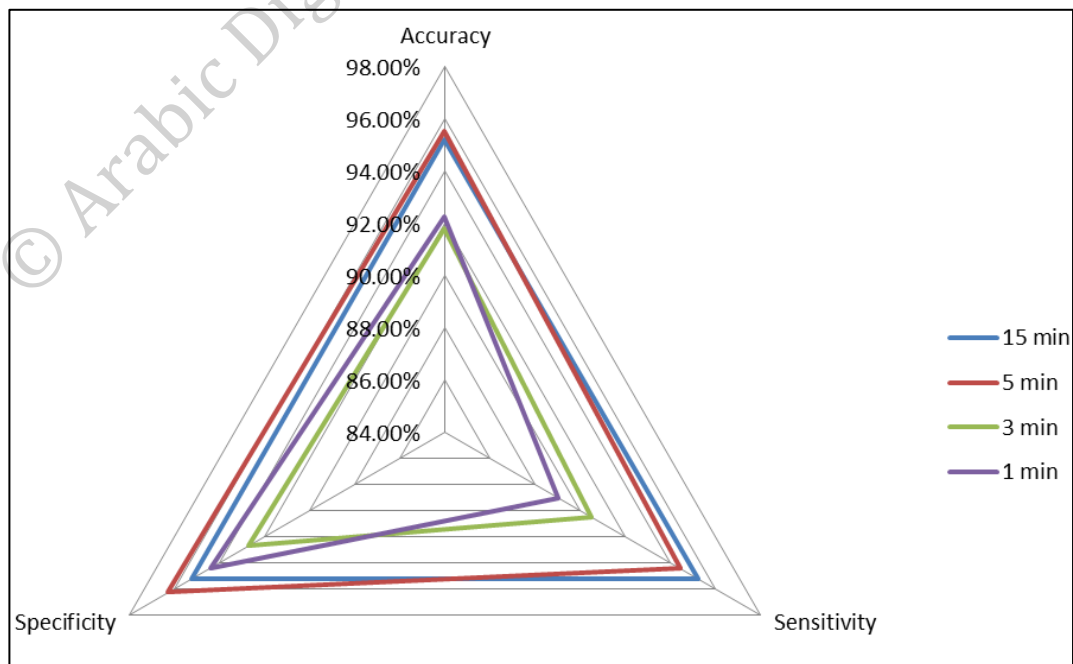


Figure 23: Ratio of accuracy, sensitivity and specificity using J48.

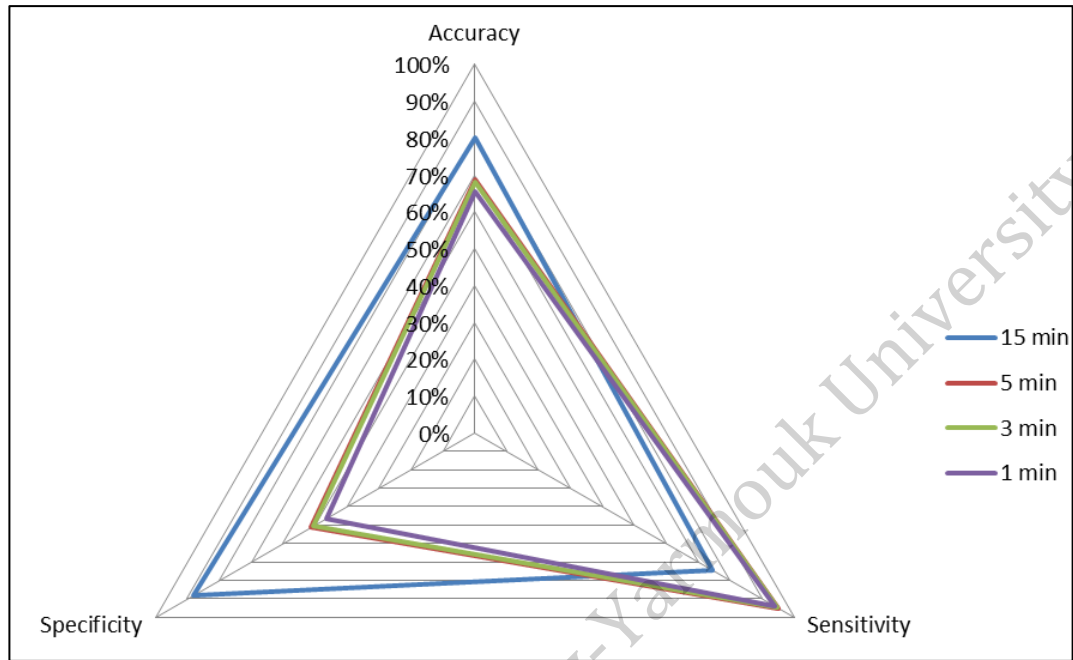


Figure 24: Ratio of accuracy, sensitivity and specificity using Naïve Bayes.

Leave-One-Out Cross-Validation method with 15 minutes signals length is also used to classify the signals. Table 11 represents the confusion matrix of SVM, J48 and Naïve Bayes classifiers using Leave-One-Out Cross-Validation method. The accuracy, sensitivity and specificity for these classifiers are reported in Table 12.

Table 11: Confusion Matrix of the SVM, J48 and Naïve Bayes using Leave-One-Out cross validation.

N = 105	Abnormal	Normal	
Abnormal	62	1	SVM
Normal	3	39	
Abnormal	60	3	J48
Normal	2	40	
Abnormal	47	16	Naïve Bayes
Normal	3	39	

Table 12: Accuracy, sensitivity and specificity measures for all classifiers.

Classification Method	Accuracy	Sensitivity	Specificity
SVM	96.19%	98.41%	92.85%
J48	95.23%	95.23%	95.23%
Naïve Bayes	81.9%	74.6%	92.85%

SVM achieved the highest accuracy, but Naïve Bayes achieved the worst results, while J48 achieved the same results as for 10-Folds Cross-Validation. The best results are obtained by using SVM in both testing options, since maximum margin property gives it advantage over the other classifiers and the overlapping between data in each class is insignificant.

5.5 Discussion

In this study a new method, for assessing fetus cardiac health, is proposed. The abdominal signal is filtered to cancel noise and correct the baseline drift. Then FECG signal is extracted and HRV signal is constructed. After construction of the HRV signal, DTCWT is used to decompose the signal. From the resulted coefficients, some statistical features have been extracted to reduce the dimension of coefficients. Finally, healthy fetus and fetus at risk are classified by SVM.

In the preliminary stages, the noise is removed and baseline drift is corrected in the abdominal signal. The output of this stage gives good results with the values as in Table 5, since it enhances the abdominal signal quality as illustrated in Figure 15.

The main problem with the independent component approach to separate MECG and FECG signals is the big differences in energy levels of required signal components. The proposed FastICA method showed better results of FECG signal extraction. Nevertheless, FastICA gives unsorted independent components, therefore it is necessary to identify which component is representing the required FECG signal. FECG signal will have the highest energy after removing the MECG signal, therefore, the highest energy signal is the required. The proposed method suppressed MECG signal and can extract FECG signal successfully. Figure 17 (a) shows the records of four channels, which is the distorted abdominal signal (i.e. the input of the FastICA) and (b), the five signals are the outputs of the method. The signals are plotted in 10 seconds duration for better orientation and clearance. It is clear that the outputs of FastICA have the FECG signal, i.e. the extraction is successful. This corresponding with the parameters settings as discussed in chapter 4.

HRV is important to detect the fetus wellbeing and to give alarms about the fetus that might be at risk. Since HRV depends on RR intervals, all of them are calculated from the extracted FECG signal. In the proposed method to calculate RR intervals, the process is started by detecting the R peaks, which are directly detected from the FECG signal. Then the calculation of RR intervals is done and finally the HRV signal is constructed. The obtained results show that HRV signal can be constructed using ECG signal recorded from the abdomen of a pregnant woman.

This study is used statistical features of HRV signal coefficients including mean, standard deviation, maximum, minimum, median, kurtosis and entropy. After calculating the features, SVM is used to predict healthy fetus. The results presented in Table 7 and Table 12 show the efficiency of these features in discriminating the healthy fetus and unhealthy fetus. The classification is done using three experiments to find out the best case to assess the fetus cardiac health.

First experiment is testing the proposed method using different classifiers; SVM, Naïve Bayes and J48. Considering the obtained results, SVM classifier has better performance in detection of healthy fetus than the other classifiers. The second experiment is the abdominal signal length, 1, 3, 5, and 15 minutes signal length are tested and the results showed that the best length is 15 minutes. The third experiment is using 10-Folds Cross-Validation and Leave-One-Out Cross-Validation, the first method is achieved best results than the second method, in spite of Leave-One-Out method is closed to the real-life applications.

Experimental results show that there are important information in HRV signal can be extracted by the proposed method and used for detection of fetus cardiac health. In addition, the proposed method investigated that 15 minutes of the abdominal signal can be used to distinguish between healthy and unhealthy fetus. Also, 5 minutes of the abdominal signal can be used but the probability is increased by 1 of miss-classification cases. Finally, our findings of detection of cardiac fetus health can help doctors to be aware of fetus health to prevent the incident and do something that saves the fetus life.

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Chapter 6

Conclusion

In this thesis, five main phases have been applied for fetus cardiac health detection. Signal preprocessing is the first phase. In this phase, the noise and baseline drift are removed from abdominal signal by a bandpass filter. The results of the proposed filter found to be satisfactory as shown in Figure 15 and Figure 16. This phase is a primary phase to present pure signal to the next phase, which is the FECCG signal extraction.

The second phase is FECCG signal extraction. The returned signal from phase one composed of MECCG signal and FECCG signal. FastICA method is used to extract FECCG signal and isolate the MECCG signal. The results of this phase contributed for good FECCG signal extraction as illustrated in Figure 17. Moreover, all FECCG signals are extracted correctly, which is an important phase for HRV signal construction.

HRV signal construction is the third phase. R peaks detection of FECCG signal is the first step and is a critical step, since the performance of the proposed method is directly influenced by the detection of R peaks. The fetus R peaks are correctly detected as shown in Figure 18 (a), Figure 19 (a) and Figure 20 (a). Then the RR intervals are calculated from the detected fetus R peaks. HRV signal is a plot represents the interval between each two consecutive R peaks in time (seconds). The long RR intervals mean that the heart pulse is dropped instantaneously. While the short RR intervals means the heart rate is raised. Finally, the cubic spline interpolation is used to construct the HRV signal as shown in

Figure 18 (b), Figure 19 (b) and Figure 20 (b). The HRV signal construction is applied on FECG signal of 15 minutes, 5 minutes, 3 minutes and 1 minute long.

Feature extraction is the fourth phase. The constructed HRV signal in the previous phase is transformed by DTCWT and the output is a set of coefficients. DTCWT characterized by shift invariance property; any small shift in the input signal cannot perturb on the wavelet coefficients. Then the features vector is constructed and is used in the fifth phase; the classification phase.

SVM, J48 and Naïve Bayes classifiers are used for classifying the cases and the comparison is done between them. From the results of the proposed method, we can write the following conclusions of the study:

- Fetus HRV signal can be constructed from abdominal signals.
- This research provides another proof that DTCWT adds reliability on the results because it is shift invariant.
- The SVM classifier gave the best results between them in all settings. When the whole signal is analyzed it achieved 97.14% accuracy, 98.14% when 5 minutes signal is used. For 3 minutes and 1 minute the method achieved 96.38% and 94.22% respectively.
- The best signal length to assess fetus cardiac health by the proposed method is 15 minutes.
- Experimental results showed that the proposed method can assess if the fetus cardiac condition is healthy or not.

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