BERK DAĞMAN

FILTERING OF MATERNAL & FETAL ELECTROCARDIOGRAM (ECG) SIGNALS WITH SAVITZKY-GOLAY FILTER AND ADAPTIVE LEAST MEAN SQUARE (LMS) CANCELLATION TECHNIQUE

NEU 2016

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A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

by
BERK DAĞMAN

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Electrical & Electronic Engineering

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Approval of Director of Graduate School of Applied Sciences

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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I commenced higher education with Near East University in 2006 and after my graduation; I was employed as an assistant at same University for Physics Laboratory and, then 2. & 3. Year Vocational school in Electronic Technologies as instructor in 2012. While I was employed with NEU, I took up M.Sc. Degree in "Filtering of Maternal & Fetal Electrocardiogram (ECG) Signals with Savitzky-Golay Filter and Adaptive Noise Canceller".

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ABSTRACT

Electrocardiogram that enroll heart's electrical action against duration is known as a bio-electrical signal. ECG is a significant diagnosis apparatus in order to detecting heart functions. Electrocardiography is explication of electrical action of the heart after a certain time, which produces a representation of Electrocardiogram. The Electrocardiogram is a very important diagnosis device in clinical application. It is particularly beneficial in diagnosing cadence diseases, alterations in electrical transmission, and myocardial ischemia and infarction. In noninvasive electrocardiography, the signal is specified by electrodes annexed to the exterior surface of the skin and saved by a apparatus exterior to the body. Electrocardiogram signal is effected by different noises kinds as movement artifacts power line attempt, etc. Electrocardiogram in noise entity is so hard to analyze and take out requisite data correctly thus to remove data correctly it is essential to filtration noise existing in signal. For filtering noise there are assorted filters are utilized. Electrocardiography area has been in existence for over a century, signal processing techniques and fast digital signal processor, in spite of substantial advances in adult clinical electrocardiography Fetal Electrocardiogram (ECG) analysis is still very new phenomenon. This is, partially owing to deficiency of availability of gold canonical databases, partially because of comparatively low SNR of fetal Electrocardiogram check against to the maternal Electrocardiogram. Fetal heart proportion and its beat-to-beat variability are two significant signs about the health and status of the fetus. The observed maternal electrocardiogram (ECG) signal consists of maternal heart signal and fetal heart signal is often very noisy. Savitzky and Golay Filter gave a procedure in order to smoothing of datum that is situated on least-squares polynomial prediction. This includes a polynomial fabrication to an input samples set and then figure out sole point polynomial within approximation spacing that means discrete convolution whose impulse response is constant. Adaptive Noise Canceller (Least Mean Square Algorithm) is an alternate process of forecasting signals damaged by additive noise or interference. In some obscured path with basic noise, the process utilizes a primary entry having the damaged signal and a reference input including noise correlated for getting signal forecast, reference entry is filtered adaptively and removed from fundamental input.

***Keywords*:** Maternal and Fetal ECG Signals; Savitzky and Golay Filter; Adaptive Noise Canceller; Least Mean Square Algorithm (LMS); Noise Effects; Denoising

ÖZET

Elektrokardiyogram (EKG) zamana karşı kalbin elektriksel aktivitesini kaydeden biyoelektrik bir sinyaldir. Kalp fonksiyonlarını değerlendirmek için önemli bir tanı aracıdır. Elektrokardiyografi belirli bir süre sonrası, kalbin elektriksel aktivitesinin yorumlanması olarak kabul edilir. EKG klinik pratikte çok önemli bir tanı aracıdır. EKG, ritim bozuklukları teşhisinde, elektrik iletimindeki değişikliğinde ve miyokard iskemisi ve enfarktüsünde yararlı olmaktadır. İnvaziv olmayan elektrokardiyografi sinyali cildin dış yüzeyine bağlı elektrotlar ile tespit edilir ve vücut dışındaki bir cihaz tarafından kaydedilir. EKG sinyali çeşitli gürültülerden etkilenir, güç hattı parazitleri ve hastanın, solunum kas veya diğer hareket tarafından üretilen, bulanık radyografik görüntüleri vb. Gürültülü EKG sinyallerini analiz etmek ve doğru bir şekilde gerekli bilgileri ayıklamak çok zordur. Bu yüzden doğru bilgileri ayıklamak için sinyal içinde mevcut gürültüleri filtrelemek gereklidir. Gürültüyü filtrelemek için çeşitli filtreler kullanılmaktadır. Elektrokardiyografi alanı yüzyılı aşkın bir süredir varlığını sürdürmektedir, sinyal işleme teknikleri ve hızlı dijital işlemcilerin erişkin klinik elektrokardiyografisinde önemli ilerlemelere rağmen, Fetal EKG analizi henüz çok yeni bir olaydır. Bu kısmen altın standart veritabanları kullanılabilirliği eksikliği, nedeniyle Maternal EKG ile karşılaştırıldığında, kısmen fetal EKG'nin nispeten düşük bir sinyal-gürültü oranı ortaya çıkmaktadır. Fetal kalp hızı ve ritmi-atıma değişkenlik, fetüsün sağlığı ve durumu hakkında iki önemli göstergedir. Gözlenen anne elektrokardiyogram (EKG) sinyali anne kalp sinyal ve fetal kalp sinyalini oluşturur ve genellikle çok gürültülüdür. Savitzky - Golay Filtre en küçük kareler için polinom yaklaşımına dayalı verileri düzeltmekte kullanılan bir yöntemdir. Bu set bir giriş örneklerinin bir polinomuna takılmasını gerektirir ve daha sonra yaklaşım aralığında tek nokta polinomu hesaplamak ayrık konvolüsyon ve dürtü yanıtının sabit olduğu anlamına gelmektedir. Adaptif Gürültü Silme yöntemi katkı gürültü veya parazit bozuk tahmin sinyalleri için alternatif bir yöntemdir. Süreç, bozuk sinyali ve birincil gürültü ile bazı bilinmeyen bir şekilde ilişkili gürültü içeren bir "referans" girdisi ve "birincil" girişini kullanır. Referans girişi uyarlamalı süzülür ve tahmin edilen sinyali almak için birincil girişden çıkarılır.

***Anahtar Kelimeler*:** Maternal ve Fetal EKG Sinyalleri; Savitzky-Golay Filtre; Adaptif Gürültü Engelleyici; En Küçük Ortalama Kare Algoritması (LMS); Gürültü Etkileri; Gürültü Temizleme

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LIST OF ABBREVIATIONS

ADC:	Analog Digital Conversion
AECG:	Abdomen Electrocardiogram
AWGN:	Additive White Gaussian Noise
BPM:	Beats Per Minute
CGM:	Continuous Glucose Monitoring
DAC:	Digital Analog Conversion
DS:	Digital Signal
DSP:	Digital Signal Processing
ECG:	Electrocardiogram
EEG:	Electroencephalography
FECG:	Fetal Electrocardiogram
FHB:	Fetal Heart Beat
HR:	Heart Rate
IC:	Integrated Circuit
LMS:	Least Mean Square
MATLAB:	Matris Laboratory
MCG:	Magneto Cardiogram
MHB:	Maternal Heart Beat
PSNR:	Peak Signal Noise Ratio
SNR:	Signal Noise Ratio
SVD:	Singular Value Dissociation
WGN:	White Gaussian Noise

CHAPTER 1

INTRODUCTION

Electrocardiography is the method that utilized to record of cardiac electrical activity for examine operation of heart muscle and neural transmission system. These electrodes specify the diminutive electrical alteration on the skin which originates from the heart muscle's electrophysiological model of depolarizing during each heartbeat.

Electrocardiogram is the transthoracic explication of the electrical action of the heart over certain duration. Analysis of ECG signal maintains information concerning the status of heart.

DSP is commit of analyzing and changing a signal to optimize or develop its activity or performance. It covers applying different mathematical and computational algorithms to analog and digital signals to generate a signal that's of higher standard than the original signal. Digital Signal Processing is mainly used to define errors, and to filter and compress analog signals in transit.

Our bodies frequently reports data about our health. This data can be received through physiological materials which measure heart proportion, oxygen saturation levels, blood pressure, nerve conduction, blood glucose, brain action and etc. Conventionally, these kinds of measurements are received at certain points in duration and marked on a patient's chart. Biomedical signal processing includes the analysis of these measurements to ensure beneficial data onto those clinicians can perform verdicts. Engineers discovered new techniques to manipulate these signals with a diversity of mathematical formulas and algorithms.

Digital filtering processes can be used for develop the signal quality and minimize fortuitous error noise ingredient.

1.1 Contribution of the Thesis

The fundamental goal of this dissertation is to monitor fetal and maternal heart based on Savitzky&Golay Filtering and Adaptive Noise Cancellation using MATLAB environment. Savitzky&Golay filter and Adaptive Noise Canceller acts as a noise canceller and their task are to extract Fetal and Maternal signal.

The contributions of this thesis include:

- Propose a system that can denoise Maternal and Fetal ECG signals for getting clear, preferable quality output signals for good recommendations.
- Intend to get hold of and extract the sectional noise influences in an appropriate way than the other techniques.
- Suggest a Denoising techniques Savitzky-Golay Filter and Adaptive Noise Cancellation Least Mean Square(LMS) Algorithm to remove all kinds of noise in Maternal and Fetal ECG signals.

1.2 Thesis Overview

Other parts of the thesis are as shown below:

- Chapter 2 is about state-of-the-art literature.
- Chapter 3 explains an overview of Electrocardiogram(ECG) signals.
- Chapter 4 presents general information about Digital Signal Processing(DSP).
- Chapter 5 gives general information related to Biomedical Signal Processing.
- Chapter 6 is about Digital Signal Filtering and Noise Reduction.
- Chapter 7 presents the most important aim of my dissertation the fundamental objective of this thesis is to monitor fetal and maternal heart based on Savitzky and Golay Filtering with Adaptive Noise Cancellation using MATLAB environment.
- Chapter 8 presents conclusions and suggestions.

CHAPTER 2
STATE OF THE ART REVIEW

2.1 Overview

State of the art review on Fetus and Maternal Electrocardiogram (ECG) signals before and during will be discussed in section 2. Because of the quite ancient history of the trouble and the generous literature in this area; it is not feasible to lid all the current techniques in their particulars. Thus because of the difficulty of the trouble, many of the available techniques have used a combination of approaches, some of that have been raised a loan from other statuses. That’s why, in this section a choice of the existing literature with private focal on the most substantial ones will be monitored, that have been especially improved for the trouble of interest.

2.2 Historic Criticism of the Fundamental Studies

In 1906 fetus electrocardiogram was first watched by M. Cremer. Initial work in this field was performed utilizing a galvanometer tool of that time; it was restricted to fetus signal very low amplitude. As measuring and amplification methods developed, Fetus electrocardiogram was more comfortable and popular (Lindsley, 1942). Restricting factor was then low fetus Signal Noise Ratio, particularly in asset of potent maternal cardiac interventions trouble that exists up to the present time. After several decades, with progresses in computer science and processing of signal methods, automatic processing of signal and adaptive filtration methods were utilized in order to fetus R-wave identification (Farvet, 1968). and maternal heart attempt annulment (Oosterom, 1986; Widrow et al., 1975). The subject matter has since been thought as a challenging trouble with a view to both signal processing and biomedical societies.

For give an opinion of previous and present study relevance in this area, publications number in fetus electro- and magneto-cardiography area, those have been listed in a free database of biomedical, international studies on health sciences, published articles, latest developments can be traced from the site named as “PubMed” (PubMed, the U. S. National Library of Medicine and the National Institutes of Health, 2008). It can be observed that after a keen peak in the 1960’s, the tendency seems to be declining until 2000.However in recent decade; interest has again rised, in particularly for fetal magneto cardiography. This should be seen as part of new low noise results, digitizing systems and, low cost measuring partly because of expansions in array signal processing and adaptive filtering procedures. It was reported which fetus cardiography is again in its initial phases and has a long way to go, in order to fulfillment fetus cardiography a clinical reliable fetus cardiac tracing means. It should further become marked which, ECG / MCG in spite of increase in research number, when standardizing number of these studies by total publications number listed in same period in PubMed, it was noted that, researchers working in ECG has fallen since the 1980s, while MCG exploratory has arrived more attention.

2.3 Goals

One of these purposes: Past works have pursued:

- Fetus heart-rate analysis
- Fetus Electrocardiogram structure science(morphology) analysis

Fetus Electrocardiogram morphology involves much more clinically data as checked against to heart rate alone. Nevertheless, because of fetal signals of low SNR, is to take a more demanding. For this reason, most of past studies have only reached in removing fetal RR-intervals utilizing R-peaks or fetal ECG waveform average crowd. Fetal ECG full morphological studies, on a rhythm to rhythm principle, are accordingly left like a challenging subject matter.

2.4 Methodology

In this section data collection and analysis will be discussed.

2.4.1 Information Picking

Fetal Electrocardiogram information collection is divided as invasive or non-invasive. Invasive procedures, recording electrodes during delivery can be achieved using only direct contact with electrode intrauterine fetal skin or scalp (Outram et al., 1995; Genevier et al., 1995; Lai & Shynk, 2002). Signals registered by invasive methods have preferred standard when compared with non-invasive techniques; however process is rather incorrect and is restricted to during labor. Nevertheless, noninvasive techniques utilize signals registered from maternal abdomen; they can be done at any gravidity step utilizing electrodes dozens. Nevertheless, low fetus Electrocardiogram Signal to Noise Ratio and other attempts are bounding factors of this process. However, owing to countless benefits of noninvasive technique, a large body of study has been acted against signal processing methods growth for revoking fetal Electrocardiogram from noninvasive records.

2.4.2 Information Analysis

These can be categorized in available literature with their fetal data analysis methodologies. Existent techniques in this field contain:

Direct Fetal Electrocardiogram Analysis

Early detection of fetal Electrocardiogram study was done on the raw data without any action. For example in (Larks, 1962). Some specific situations were notified in that because of vertex fetus introduction, fetal R-peaks come in sight as positive summits whilst maternal summits had negative summits. Fetal RR-spacing detection is quite easy and may be succeed by easy peak detection, in similar situations, already devoid of maternal Electrocardiogram elimination. Nevertheless, these techniques are not every time possible and it is highly dependent fetal representation and gestational age.

Adaptive Filtration

Adaptive filters distinct kinds have been utilized in order to maternal Electrocardiogram extraction and fetal Electrocardiogram extraction. These techniques include of teaching an adaptive or matched filter in order to either eliminating maternal Electrocardiogram utilizing one or different maternal reference channels (Widrow et al., 1975).or directly training filter for removing fetus QRS waves (Farvet, 1968; Park et al., 1992). Particular, adaptive filters like ‘part based weighted sum filters’ (Shao, et al., 2004). And least squares error components (Martens et al., 2007). It is also used for this purpose. Available adaptive filtration techniques for maternal Electrocardiogram artifact dissipation, either suppose a reference electrocardiogram of maternal channel which is morphologically alike to infecting wave, or request different in linear free channels to approximately rebuild any morphologic figure from three references. Both of these entries are in practical improper and with restricting efficiency, since maternal morphology of Electrocardiogram polluters highly depend on electrode positions and it is not all the time feasible to rebuild serve out maternal Electrocardiogram morphology from reference electrodes linear combination. For this reason, a maternal Electrocardiogram extraction technique which would not essential for any surplus reference electrodes or at most an individual reference out of morphologic resemblance is excellent relevance limitation.

Linear Dissociation

Single or multi-channel dissociation inputs are alternative extensive interference. In this process, signals are dissociated into several constituents by utilizing appropriate base functions. Base functions can be chosen from classes which are in any wise in accordance with time, frequency, or fetal ingredients scale properties. Wavelet dissociation (Li et al., 1995; Khamene & Negahdaripour, 2000). And matching chases (Akay & Mulder, 1996). Are between these techniques. Spatial filtering methods like singular value dissociation (SVD) (Damen & Van Der Kam, 1982; Kanjilal et al., 1997; Van Oosterom, 1986; Vanderschoot et al., 1987). Sightless and semi-sightless source segregation (Zarzoso et al., 1997). Can be marked as 'information-driven' dissociation processes, that is establish necessary merits functions from information itself, by maximizing any signal statistical measurement segregation. In (Zarzoso & Nandi, 1999; Zarzoso & Nandi, 2001). It has became indicated which in order to fetus Electrocardiogram subtraction sightless resource allocation techniques outperforms adaptive filters like proposed as. Spatial filtration benefits over traditional adaptive filters are which they can additionally distinct maternal and fetus complicated with transient crossover. Various versions of sightless and semi-sightless source segregation processes have been utilized for fetus Electrocardiogram subtraction. These techniques are usually based on free components guess for maternal and fetus signals or some transient presence construction for wanted signals. Sightless source separation techniques have also been jointed with wavelet dissociation in order to remove and noise reduction of fetus Electrocardiogram signals (Vigneron et al., 2003; Jafari & Chambers, 2005). Dissociation processes are newly most joint and efficient fetus Electrocardiogram subtraction way and noise reduction. But, present techniques are rather general and have not been completely customized to periodical Electrocardiogram constructions. Accordingly, a challenging matter is to propose multichannel processing of signal techniques (linear or nonlinear) which are particular to Electrocardiogram / Magneto cardiogram signals.

Nonlinear Dissociation

Linear dissociation processes utilizing either constant the merits functions (e.g. wavelets), or information-driven principle functions (e.g. singular vectors) possess restricted performance for nonlinear or signal and noise corrupt admixture. Actually, fetal signals and another attempts and noises are not every time ‘linearly separable’.

A remedy for this type of situation, non-linear transformation use to separate signal and noise research components. Definitely, nonlinear transforms are rather special and need some previous data about requested and undesired signal portion.

Maternal Electrocardiogram subtraction series and fetus Electrocardiogram rising techniques have been improved. These techniques take place utilizing noisy signal and its delayed types in order to establish a state-space signal statement, smoothing state-space trajectory utilizing traditional or Principal Component Analysis smoothers (Kotas, 2004). And transporting samples back to time domain explanation. These techniques are very appealing from point which they are possible to as few as one sole channel of maternal abdominal. But, necessary time-lags choice is experimental and significant inter-beat cardiac signals variations can be removed throughout state-space smoothing. Even, compared to linear techniques have higher computational complication.

2.5 Advanced Forming versus Reverse Solutions

Noninvasive cardiac signal significant view works (either for adults or fetuses) is to find relationships among cardiac potentials formed at heart level and potentials listed on body surface. This problem is familiar as electrocardiography forward problem, for that electromagnetic basises are utilized with cardiac potentials electrophysiological patterns and volume transmission patterns, to give notice potentials which can come in sight on body surface. Advanced forming also protects precious ideas for anticipating more practical problem heart potentials from body surface registrations that is reverse solution. Advanced and reverse difficulties have long been worked in order to adult heart signals (Gulrajani, 1998). However, this type of fetal heart signals there are only few studies. In a more recent study, fetal Magneto cardiogram and Electrocardiogram credibility problem has been studied utilizing advanced forming in normal and pathologic situations. They utilize several patterns for different stages of pregnancy. Particularly, pregnancy last trimester in advanced forming, they noted vernix caseosa layer having two holes and obtained fetal Electrocardiogram maps which looked alike real measured maps. Bores in vernix caseosa were noted over of fetus mouth and umbilical cord start, appropriate to the 'preferential' current pathways. On the other hand, for their actual information working, they utilized simple techniques like maternal Magneto cardiogram average waveform extraction.

2.6 Alternate Measurement Methods

Electrocardiography in past studies, including fetal heart prosperity has been observed with other methods:

Echocardiography; Additionally acknowledged as heart sonography that is based on canonical ultrasound processes.

Phonocardiography (Zuckerwar et al., 1993; Kovacs et al., 2000; V´arady et al., 2003). Is heart sounds graphical recording and murmurs manufactured by cardiac contraction (containing its valvule and related large veins), taken as pulsations and converted by a microphone of piezoelectric crystal into a changing electric output in accordance with pressure, it presented with sound waves.

Cardiotocography; is uterus narrowing with a pressure precision transducer, and fetal heart synchronous measurement ratio with an ultrasound transducer, in order to measure strength and uterus narrowing frequency.

Magnetocardiography (Kariniemi & Hukkinen, 1977; Chen et al., 2001; Ter Brake et al., 2002). Is a method like Superconducting Quantum Interference Device (Clarke & Braginski, 2006). To gauge cardiac signals magnetic fields utilizing highly sensitive tools.

Between techniques mentioned above, echocardiography is most widespread and commercially most existing fetus cardiac tracing means. Even so, Electrocardiogram and Magneto cardiogram include more data, since most heart anomalies have some perspicuity on Electrocardiogram/Magneto cardiogram morphology or RR-interval timing (Peters et al., 2001). Actual study is accordingly focused on Electrocardiogram and partly Magneto cardiogram that is Electrocardiogram magnetic counterpart. Note that because of Magneto cardiogram and Electrocardiogram morphologic resemblance, Magneto cardiogram processing techniques are analogous to Electrocardiogram-based ones; despite utilizing current Superconducting Quantum Interference Device technology for magnetic registering, fetal Magneto cardiogram Signal to Noise Ratio is generally higher than its

Electrocardiogram. But, nowadays Electrocardiogram recording tool are straightforward and more purchasable when compared with magneto cardiogram systems.

2.7 Present Problems and Problem Description

Pass in review previous studies, it can be noticed that considering opulent literature, there are still A few basic elements which request upwards works. Following prior statements, between distinct data collection setups, it is condensed on Electrocardiogram situated systems utilizing multichannel noninvasive maternal abdominal measurements, and purpose is to recall fetus Electrocardiogram morphology with maximum feasible stability, in accordance with for morphological works. In this case, bounding factors and challenging signal processing subject matters contain:

- Fetus cardiac potentials Weakness and low-conductivity layers circumambient fetal that is lead to low amplitude fetus Electrocardiogram at maternal body surface;
- Maternal Electrocardiogram high venture, uterus narrowing, maternal respiratory, and movement artifact signals;
- Fetus probable motions and requirement in order to sort of fetal cardiac signals ‘standard presentation’ as far as concerns fetal body axis;
- Automatic operations Expansion which can be implemented on long datasets with least mutual effect with specialized operators; supplying trust measures for conjectural cardiac signals and finding theoretical limits for ‘recoverable data’ quantity noise body surface being recorded.

Even if, traditional ECG filtering techniques are normally based on a time measurement, frequency, or signals and noise scale-separability, it is joint to all noise reduction methods. Nevertheless, cardiac signals have upwards pseudo-periodic construction that it is trusted; have not been well-utilized in Electrocardiogram noise reduction layout. In prior works multichannel dissociation techniques have been frequently implemented to sighted signals rather ‘imprudently’ and there is usually no warranty which fetus components are removed as apart elements. For this reason, a significant subject is to improve removing fetal components probability and also to develop removed components quality, through suitable preprocessing and utilizing previous data about signal noise mixtures. This is an essential step in order to upgrade robust fetus Electrocardiogram /Magneto cardiogram subtraction algorithms. Linear dissociation techniques are very reciprocal, not only owing to linear pattern currency itself; however further for these versions simplicity. But, as consulted before, there are states in that requested signals are not lineal sectional and nonlineal dissociation is indispensable. Consequently, an intriguing work area is to associate lineal and nonlineal methods to utility from lineal transformations convenience and strength of nonlinear technique simultaneously. Alternative concerned matter is to find physiological hermeneutics for elements removed by multichannel source segregation methods. While these techniques are often rather abstract statistical criteria on the basis of maximization like statistical independency, it is not very clear what resultant elements to be physical communicate to, when implemented to actual information. For heart signals, this subject is very important, when we imagine which cardiac is a deployed resource and not a punctual resource. Fetal Electrocardiogram Morphologic forming is another subject of interest. While prior fetal Electrocardiogram /Magneto cardiogram patterns condense on advanced patterns based on electromagnetic and volume transmission theories (Oostendorp, 1989; Stinstra, 2001). In order to appraise processing of signal methods situated on body surface potentials, more abstract patterns are necessary. Essentially, for estimate and compare sole or multichannel processing methods, we require patterns which ease us to operate simulated signals processing of signal appearances as their morphology, RR-spacing timing, fetus status, dimensionality, and Signal to Noise Ratio, without going into signal spread particulars and volume transmission theories. For adult Electrocardiogram, like these models example was improved in [39], where individual channel adult Electrocardiogram was modeled with a dynamic pattern. Nevertheless, present patterns have not noted Electrocardiogram multi-dimensional nature and are not suitable for multichannel processes assessment which utilize various channels' mutual data'.

2.8 Summary

In this part, fetus heart signal extraction literature and its challenging subjects was briefly discussed. It was exclusive which in present work, we are interested in this issue developing processing of signal views, for simplify fetus heart signals subject.

CHAPTER 3

AN OVERVIEW OF ELECTROCARDIOGRAM(ECG) SIGNALS

3.1 Overview

Electrocardiography is a technique which records electrical action againts time. The alters in the difference of electrical potential between two points (voltage) throughout myocardial fibers depolarization and repolarisation are registered by electrodes established on chest surface and limb. Electrical potentials sources are contractible cardiac muscle celss. Electrocardiogram curve showing a wave shape at a given time is either printed upon squared paper which operates at a immutable impetus or indicated on a computer display. Electrocardiography benefits come with its relatively inexpensive, urgent validity and easy application. Operation itself is further non-invasive.

ECG is utilized for research some abnormal cardiac function types containing arrhythmias and transmission inconveniences as well as cardiac morpology. It is also beneficial for defining Pacemaker performance.

3.2 Heart Electrical Transmission System

Heart muscle is created from two primary cell types:

- Cardiomyocytes, that form electric potentials in course of narrowing
- Cells specialized in production and action potentials transmission.

This particular electric cells automatically depolarized. Rest of cardiomyocytes polarized with significantly lower speed of an electric membrane. This means there is a lag among two signals arrival, thus which when second impulse reaches, cells are no longer resistant (Kavitha & Christopher, 2014).

Waves, Sections and Spacings

In Electrocardiogram waveform there are specific components

Baseline: A supine line when there is no electric action on electrocardiogram.

Sections: Baseline line duration among waves.

Spacings: Duration among same contiguous waves sections.

P-wave is initial Electrocardiogram deviation. It outcomes from atria depolarization. Atrial repolarisation take shapes in depolarization of ventricular course and is uncertained. QRS complicated communicates to depolarization of ventricular.

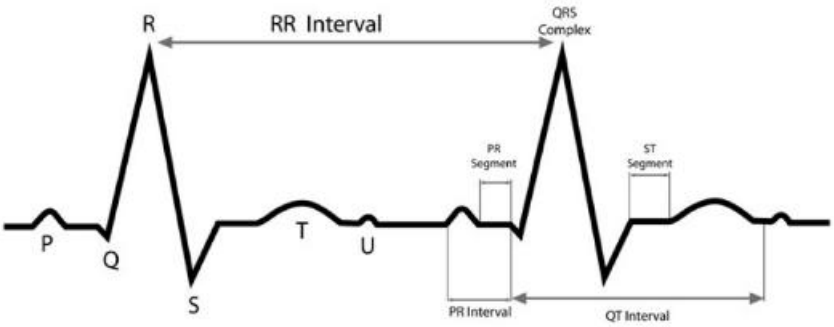


Figure 3.1: Electrocardiogram waves, sections and spacings (Kavitha & Christopher, 2014).

T-wave symbolizes repolarisation of ventricular, i.e, resting membrane renovation potential. Approximately one quarter of population, U-wave can be viewed after T-wave. This usually has identical polarity as previous T wave. It has been proposed which U-wave is reasoned by after potentials which are likely created by mechanical-electrical feedback. Reversed U-waves can come into view in left ventricular hypertrophy asset or is chaemia.

Section of PQ gets into touch to electrical urges delivered through node of S-A, his bunch, its branches, fibres of Purkinje and is generally isoelectric. Spacing of PQ states time passed from atrial depolarization to ventricular depolarization initiation. Gap of ST-T encounters with leisurely and quick repolarisation of ventricular activity potential and repolariastion. Then TP spacings is duration for that atria and ventricles are in diastole. Gap of RR symbolizes one cycle of heart and is utilized to compute ratio of cardiac.

Normal Heart Rates

Heart Rate of 60 – 100 BPM is NORMAL

HR > 100 bpm = TACHYCARDIA

Tachycardia is a heart rate which is in excess of the normal resting rate generally, an endurance heart rate over 100 beats per minute is adopted as tachycardia in adults.

HR < 60 bpm = BRADYCARDIA

Bradycardia is a slow heart rate, described as a heart rate of under 60 bpm in adults.

3.3 Hermeneutics of the Electrocardiogram

After defining dominant cardiac rhythm, mean electrical axis and heart location in chest, subsequent step of Electrocardiogram analysis is to comment form, amplitude and waves, sections and spacings time.

P-Wave

P wave is normally positive in main ends. It can occasionally have negative deviation in ends III and VI or is biphasic in these ends and in end a VL. P-wave normative period is no longer than 0.12s and voltage in limb ends should not in excess of 0.25 and 0.15 mV in precordial ends.

T-Wave

T-wave should be positive in main ends apart from for a VR and occasionally in VI, in that it may be negative or horizontal. Extremely negative T-waves can be MU sign, for instance by left anterior descending artery congestion virtue. Other cases contain cardiomyopathy of hypertrophic and haemorrhage of subarachnoid. T-wave inversion occasionally take shapes without clear reasons.

Electrocardiogram signals are specular electrical actions of a cardiac muscle. ECG are concerned to nested diversity and methods of complicated chemical electrical and mechanical available in cardiac. They conduct a great deal to diagnostic data of precious solely defining heart functioning but further other systems like circulation or nervous systems.

Electrocardiogram signal for over 100 years has became a issue of works. Initial electrical activities cardiac record was achieved by an August Waller who is English physiologist utilized surface electrodes established on a skin and bonded to electrometer of capillary in 1887. August Waller was initial to call recorded signal ECG. Even so Willem Einthoven is reputabled to be Electrocardiography father, who in 1902 registered first ECG with a string galvanometer utilize. M. Cremer provided first esophageal ECG recording with help of private esophageal electrode in 1906 (Berbari, 2000).

This kind of Electrocardiography has been extremely improved in 1970's of last century to be utilized as a method beneficial in atria rhytm irregularity differentiation. Cremer registered further initial fetus ECG. Willem Einthoven got Nobel Prize for electrocardiography innovation and its growth in 1924. Since then there has became a significant exploratory in electrocardiography field. Electrocardiography has became a customary technique in cardiac diagnostics since 1940s. There has been a important diagnostic growth methods based on Electrocardiogram analysis.

Electrocardiogram signal is one of most well-known biomedical signal. Its high diagnostic abilities have been indicated. In recent years there has became a important interest expansion in efficient techniques growth of processing and electrocardiogram signals analysis with intent formation diagnostic data beneficial. Those chasing have been carried out in parallel with data technologies, specially in digital signal processing area carried out both in hardware and software. In merit of Electrocardiogram signals principle, they frequently have been a imprecise data source. In systems of diagnostic design, it becomes of intereset for making them user friendly. These factors have interest of triggered in Computataional Intelligence technology parlay. In this situation, it is woeth recalling which first works in systems of intelligent field go back to Artificial Intelligence methods utilize with a its symbolic processing wealth. Electrocardiogram signals definition in terms of symbols sequences, that are investigated and categorized based on official grammars machinery.

One of first initiatives, that fully exploits Artificial Intelligence methods, comes in semantic nets form implemented to Electrocardiogram signals analysis. In this process signal is symbolized in a OR/AND graph form while sorting method is interested with a graph search. Another significant methods collection stems from rule based notion systems where an Electrocardiogram signal is defined in “if-ten’’ rules format. Decision mechanism is believed to utilize supposed modus ponens. Confidence on this notion, although, requests which a information basis is literally which for any signal there is a rules set to be utilized in the illation technique. Rule base size drop along with an increase of reasoning processes achieved in ambiguity asset becomes feasible when summoning a thus named universalized modus ponens.

Electrocardiogram processing of signal and analysis involves a order of steps between that most needed include;

- Signal Amplification and its A/C transformation
- Noise Removal
- Property choice

The quality and influence of techniques utilized at these stages mention entire process quality of grading and Electrocardiogram signals explication. Both amplification of signal and A/C transformation are executed in hardware while entire filtration and noise cancellation are executed through information processing improved technologies utilize.

3.4 Electrocardiogram Signals Nature

Electrocardiogram signals are specular heart electric action. Electrocardiogram signal is some type of an electrical provocation effuse in cardiac muscle cells. Under sway of this provocation, cells of cardiac muscle miniaturize, that consequently, reasons a mechanical influence in heart atria cyclic towing form and ventricles. As an cardiac muscle towing influence, blood disseminates in human organs.

Spread electrical provocation in cardiac muscle creates a depolarization bioelectric potentials adjacent heart cells wave, depolarization wave diffusion. After depolarization wave moving, cells of cardiac muscle turn to their rest situation rescuing before starting resting negative potential. This situation is named a repolarisation phase.

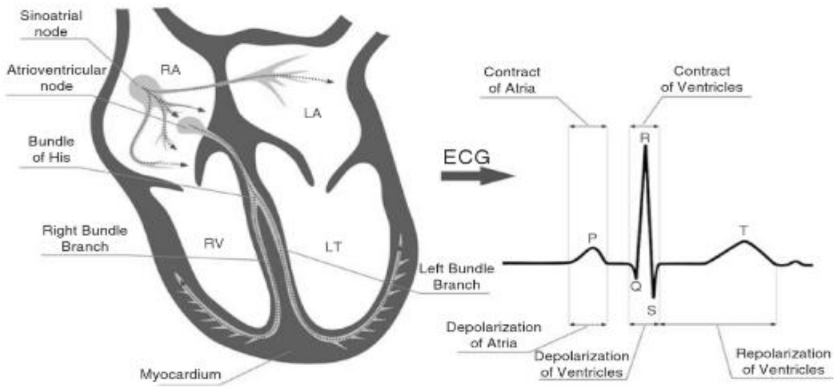


Figure 3.2: Wave of depolarization in heart muscle spread (Berbari, 2000).

3.5 Electrocardiogram Signals Processing & Analysis

In cardiology Electrocardiogram signals form a significant diagnostic datum source. For getting benefit from it, signals have to became appropriately recorded and processed in such a way which we can continue with their efficient analysis and interpreation. Electrocardiogram signals are comparatively low quasi-periodic several mV amplitude. They are frequently influenced by noise. Signal requests recording their amplification and also processing for compress noise to highest scope. Furthermore Electrocardiogram signal analysis is achieved based on these registrations in order to that noise has became depressed. Entire processing initial stage is an Analog to Digital Conversion(ADC). Subsequently digital Electrocardiogram signal is filtered in order to clear noise and also processed to develop property choice techniques influence, grading and explication implemented to signal. Data granulation has been taken into account as one of intersting and encouraging options In this context; in substance techniques arising there can be sought in a way materialization way data compression specific method.

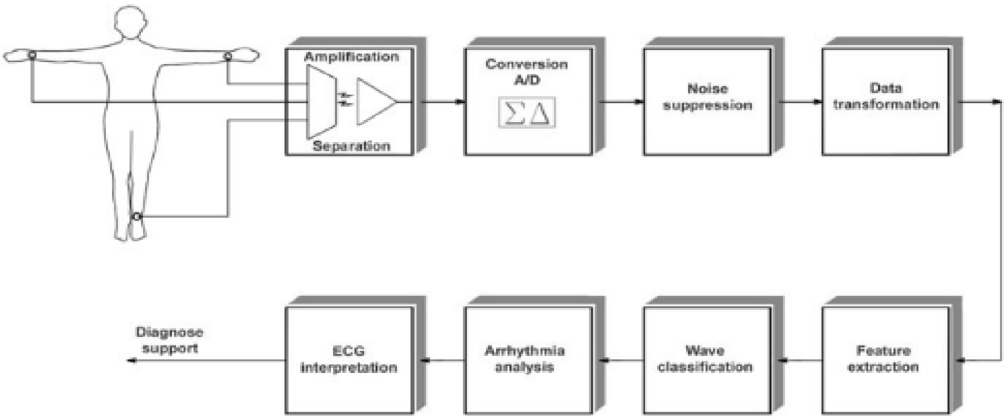


Figure 3.3: Primary stages of electrocardiogram signal processing and analysis(Berbari, 2000).

3.6 Processes for Recording Electrocardiograms

Electrocardiogram is registered by placing an electrodes array at particular places on body surface. This is feasible because heart is suspended in a conductive medium. Figure 3.4 indicates the ventricular muscle within the chest. When one section of the ventricles depolarizes and for this reason being negative concerning the remainder parts of the heart, forming a potential difference.

Electrical currents flow from depolarized field to polarized field in great ways. It is this electrical field which can be gathered under surface of the heart.

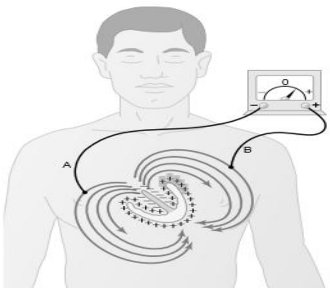


Figure 3.4: Current flow in chest throughout partly depolarized ventricles (Berbari, 2000).

3.6.1 Electrocardiographic Ends

Traditionally, electrodes are established on each arm and leg, and six electrodes are replaced at described locations on chest. Three fundamental kinds of Electrocardiogram ends are registered by these electrodes set:

- Canonical bipolar limb ends
- Chest ends
- Augmented limb ends.

The limb ends are applied as bipolar ends because each end utilizes a single pair of positive and negative electrodes. Augmented ends and chest ends are unipolar ends because they have a single positive electrode with other electrodes coupled with each other electrically to serve as a joint negative electrode.

Three Bipolar Limb Ends

Figure 3.5 indicates electrical links between patient limbs and electrocardiograph for recording ECGs from so-called canonical bipolar limb ends. In these regulations ECG is registered from two electrodes established on heart dissimilar sides, in this instance, on limbs. Three different connections are feasible,

- End I
- End II
- End III.

End I in registering limb End-I, electrocardiograph negative terminal is connected to right arm and positive terminal to left arm.

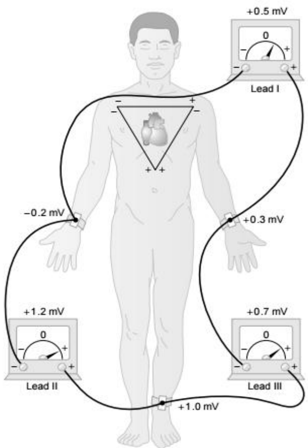


Figure 3.5: Electrodes traditional regulation for registering standard electrocardiographic ends. Einthoven's triangle is superimposed on chest (Berbari, 2000).

Accordingly, the electrode of the right arm is electronegative concerning the electrode of the left arm. The electrocardiograph registers a positive signal, which is, above zero voltage reference line in ECG. When opposite is true, electrocardiograph registers below this line. End II to register limb end II, electrocardiograph negative terminal is connected to right arm and positive terminal to left leg. Consequently, when right arm is negative according to left leg, electrocardiograph registers positively. End III to register limb end III, electrocardiograph negative terminal is connected to left arm and positive terminal to left leg. This means which electrocardiograph registers a positive signal when left arm is negative according to left leg. These three limb ends coarsely form an equilateral triangle with heart at the center, refer to Figure 3.6.

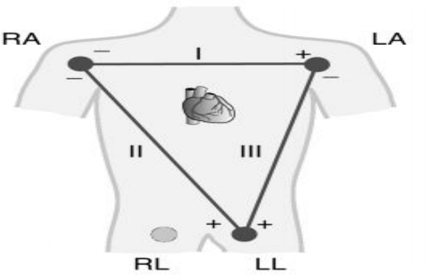


Figure 3.6: Einthoven triangle with canonical electrocardiogram limb ends placement and of positive and negative place registering electrodes for each of three ends. RA, right arm; LA, left arm; RL, right leg; LL, left leg Adp. (Berbari, 2000).

This triangle is named Einthoven’s triangle in respect of Willem Einthoven who improved Electrocardiogram in 1901. Two vertices at triangle upper part symbolize points at that two arms are electrically connected, and lower vertex is electrode located on right leg used as a ground point. Depending on the end used to record the Electrocardiogram signal, the resultant shape is slightly different; these differences can be monitored in Figure 3.7. In the three electrocardiograms indicated in Figure 3.7, it can be seen, which at any given instantaneous potentials sum in ends I and III equals potential in end II, therefore exemplify availability of Einthoven’s law. Signals from these ends are uniform between them, it does not substance greatly that end is registered when one wants to diagnose various cardiac arrhythmias, because arrhythmias diagnosis depends primarily on time relations between cardiac cycle various waves.

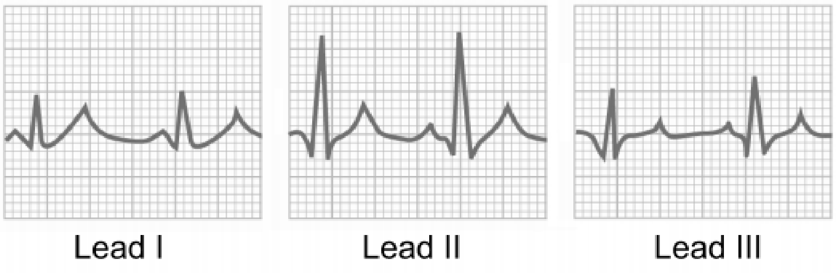


Figure 3.7: Normal ECGs registered from the three canonical electrocardiographic ends (Berbari, 2000).

Chest Ends When it is significant to diagnose damages in ventricular or atrial muscles, or in Purkinje conducting system, the three Bipolar Limb ends records are not beneficial. For these cases, we need ends which can show cardiac muscle abnormalities narrowing or cardiac impulse conduction in these areas. Chosen ends for diagnose these cases are the chest ends, also called Precordial Ends, that are represented in Figure 3.8. These ends are used to record Electrocardiogram with one electrode replaced on front chest surface immediately over heart at one of the points given in Figure 3.8. The distinct registrations are acknowledged as ends V1, V2, V3, V4, V5, and V6. This electrode is connected to electrocardiograph positive terminal, and negative electrode, named the unregistered electrode, is connected through equal electrical resistances to right arm, left arm, and left leg, all concurrently. Generally these six canonical chest ends are registered, one at a time, where chest electrode is being replaced in order at six points illustrated in figure. Figure 3.9 shows healthy heart ECGs as registered from these six canonical chest ends. Each chest end registers primarily cardiac musculature electrical potential directly under electrode, because heart surfaces are close to chest wall. For this reason, comparatively minute abnormalities in ventricles, especially in anterior ventricular wall, can reason evident changes in ECGs registered from separate chest ends.

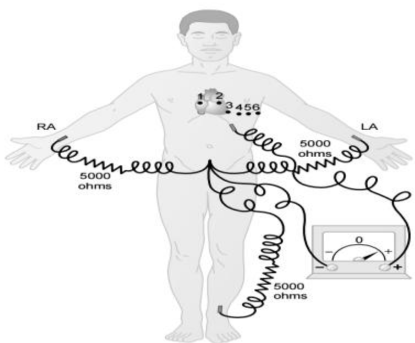


Figure 3.8: Body connections with electrocardiograph for recording chest ends LA, left arm; RA, right arm (Berbari, 2000).

3.7 Physiological Principle

Human heart is created of myocardium. When activity potential take shapes, it will end to a myocardial narrowing. Then heart pumps blood to all body. By the way, the current resulting from activity potential will spread from heart to all body unequally. It clarifys why we can keep the signal from the various parts of human body by surface electrodes. The measured waveform is named electrocardiogram. And a end is created by potential waveforms registered from the electrodes replaced on different parts of body. Based on cardiac potential axis, there are six standard ends, containing End I, End II, End III, "a V_R," "a V_L" and "a V_F". Right foot is generally taken into account as a reference ground. His potential amplitude alters less than all other refererence points because it's farthest from heart. Actually, the systole of heart is not fully controlled by automatic nervous system, but essentially by the specialized cells in Sinoatrial node that works like a pacemaker. The organized potential from sinoatrial node will spread to all atria and t make it contracted. Then, when contracted, atria pumps the blood into the ventricles. By the way, passing through the atrioventricular node between the ventricle and atrium, action potential will enter to all areas of the ventricles via Purkinje fibers, then makes the it contracted. Eventually, Ventricle pumps the blood to the arteries.

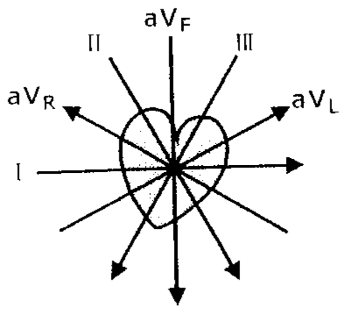


Figure 3.9: Cardiac potential axes suitable to various electrocardiogram ends. (Berbari, 2000).

When the nervous impulses pass through the atrium and ventricle, the electrical current will extended to the cardiac tissue and induces the production of the myocardial activity potential. Some portions of action potential can be defined on the surface of skin. That's why it's possible to measure the change of action potential when we establish electrodes on the surface of body. Certainly, those electrodes should be replaced on the area suitable to heart. The time-varying potential recorded is Electrocardiogram. And a cardiac vector is a type of projection of potential on the front plane surface of body. There is 60 degrees among each two axes composed by projected vectors. Each axe symbolizes a end that has no relation with the position of electrodes. The phenomenon is explored by a Holland physiologist Willien Einthoven. It is also named Einthoven’s triangle.

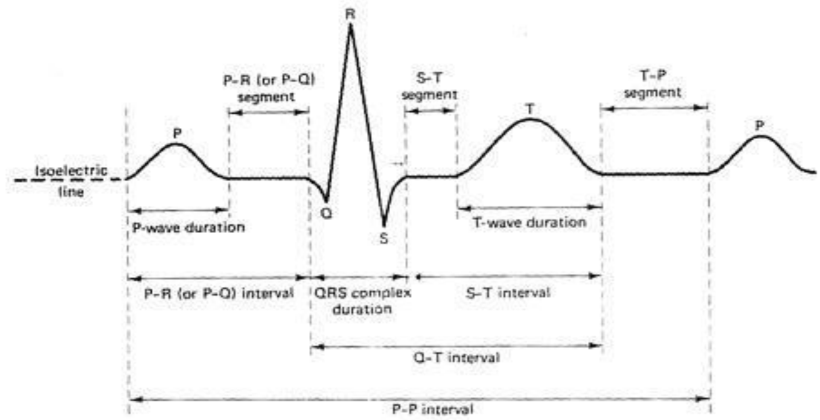


Figure 3.10: Timing and wave amplitudes of ECG (Berbari, 2000).

3.8 Electrocardiogram Noise Contributions

Having knowledge how noise is presented into an ECG signal is very significant for good consultations, because which is what we want to be able to filter out. We must define the type of noise in the Electrocardiogram signal and then choose a filtering algorithm suitable for dealing with it. Noise can comprise in multiple different forms. Some examples are dedicated below:

- Electrical venture from power lines add 50 or 60 Hz power-line frequency.
- Muscle narrowing and muscle action can compose high frequency Electromyography noise.
- Movement artifacts like motion of the electrode over the skin surface.
- Impedance changes at the skin/electrode interface because of transient loss of contact or unsecured electrodes.
- Baseline drifts because of respiration.
- Noise presented because of instrumentation or electronic apparatus

3.9 Summary

Electrocardiogram is a skin-surface measurement of electrical vector created by heart with each heart beat. Cells have “automaticity” which reasons them to fire at orderly intervals. Potentials created by these cells flow from one side to other heart muscle (myocardium) in presumable patterns to create Electrocardiogram waveform measured on skin.

CHAPTER 4
DIGITAL SIGNAL PROCESSING (DSP)

4.1 Overview

World of Science and Engineering is completed with signals, by a majority situations, these signals to generate sensory information from actual world as it is:

- Seismic vibrations
- Visual images
- Sound waves
- Images from remote space probes
- Voltages created by cardiac and brain
- Radar and sonar reflections
- Numerous distinct implementations.

Processing of Digital Signal is mathematics, algorithms, and processes utilized to manage these signals later they have been transformed into a digital shape. This contains a broad diversity of aims, like:

- Development of visual images
- Identification and speech production
- Information compression in order to storage and transfer, etc.

  Processing of Digital Signal is science of utilizing computers to resolve these information types. This contains a broad diversity of aims:

- Filtration
- Recognition of speech
- Enhancement of image
- Compression of data
- Neural Networks
- and further.

4.2 What is a Signal?

Anything that carries data is a signal. e.g. human voice, smoke signals, fragrances of the flowers, chirping of birds, gestures (sign language). Most of our body functions are organized by chemical signals, sightless people utilize sense of touch. Bees get into touch by their dancing pattern. Modern high speed signals are: voltage changer in a telephone wire, the electromagnetic field infiltarating from a transmitting antenna, change of light density in an optical fiber. So we see which there is a nearly infinite diversity of signals and a large number of paths in that signals are transported from on place to distinct place.

4.2.1 Signals: The Mathematical Path

A signal is a actual (or complex) worth function of one or more actual variable(s). When function depends on a individual variant, signal is one-dimensional and when function depends on two or more variants, signal is multidimensional.

Examples of one-dimensional signal:

A speech signal, daily maximum temperature, yearly rainfall at a place.

Example of two-dimensional signal:

An image is a two dimensional signal, vertical and horizontal coordinates typify the two dimensions.

Example of four-dimensional signal:

Our physical world is four dimensional (three spatial and one temporal).

4.3 Processing of Signal

Processing signifies operational in some style on a signal to clean some beneficial data e.g. we utilize our ears as input apparatus and then auditory pathways in the brain to remove data. The signal is commited by a system. In the example referred above, in nature the system is biological. The signal processor may be an electronic system, a mechanical system or already it might be a computer program.

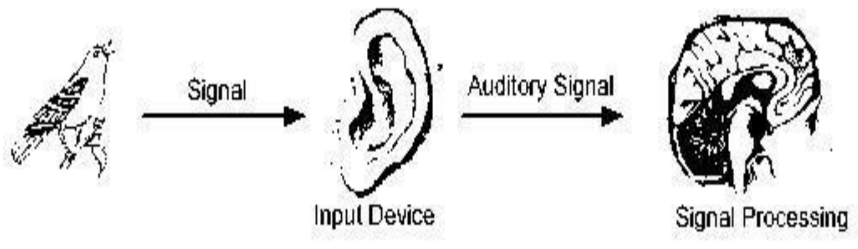


Figure 4.1: Biological signal in nature (Smith, 1999).

Analog towards DSP

Processing of signal managements interpolated in many implementations as instrumentation, control and communication systems, processing of biomedical signal etc. can be applied in two various methods:

- Analog or continuous time technique
- Digital or discrete time technique

Analog Signal Processing

- Utilizes analog circuit components like resistors, capacitors, transistors, diodes etc.
- Based on natural capability of the analog system in order to solve differential expressions which define a physical system.
- The solutions are got in actual time.

DSP

In Digital Signal Processing "Digital" stands for which the processing is done either by a digital hardware or by a digital computer.

- Trusts on numerical calculations.
- The technique may or may not give outcomes in actual time.

The benefits of digital attempt over analog attempt

- *Resilience:* Same hardware can be utilized to do different type of signal processing operations, while in the case of analog signal processing one has to design a system for each type of process.
- *Repeatability:* The same signal processing operation can be repeated again and again giving same outcomes, while in analog systems there may be coefficient variation because of alteration in temperature or supply voltage.

The selection among Analog or DSP depends on the implementation. One has to compare design duration, size and the price of the application.

4.3.1 Discrete Time Signal Processing and Digital Signal Processing

When we utilize digital computers to do processing we are doing digital signal processing. However mainly the theory is for discrete time signal processing where dependent variant usually is continuous. This is owing to the mathematical simplicity of discrete time signal processing. DSP attempts to apply this, as intimately as possible. So what we study is frequently discrete time signal processing and what is truly applied is digital signal processing.

4.4 The Width and Profundity of DSP

DSP is one of the strongest technology to create a science and engineering in 21. century. Revolutionary modifies have anyway been made in a wide range of areas:

- High fidelity music breeding
- Radar & sonar
- Oil prospecting
- Communications
- Medical imaging

Each of these areas has improved a profound Digital Signal Processing technology, with its own mathematics, algorithms, and specialized methods. This width combination and profundity makes it not possible for any one separate to main as a whole Digital Signal Processing technology which has been improved. Digital Signal Processing education includes two duties: learning generic notions which apply to the area like an all, and learning appropriated methods for your special field involvement (Smith, 1999).

4.5 Fundamental Components of a DSP System

Mainly the signals matched in science and engineering are analog in nature. Which are the signals are functions of a continuous variant, like time or space and generally take on values in a continuous range. These kinds of signals may be processed directly by suitable analog systems (such as filters or frequency analyzers) or frequency multipliers for the aim of changing their properties or removing some desired data. In such a status we say that the signal has been committed directly in its analog form, as defined in Figure 4.1. Both the input signal and the output signal are in analog form (Prandoni & Vetterli, 2008).

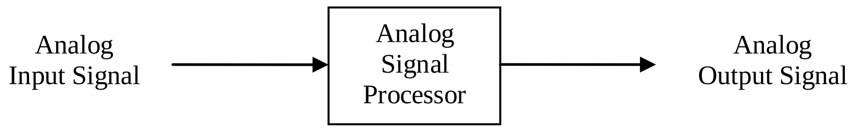


Figure 4.2: Analog signal processing

4.6 Primary Notions of DSP

Digital Signal Processing technology and developments greatly affects everywhere in modern society. In the absence of Digital Signal Processing, we would not have digital recording; digital internet audio or video; Compact Disc, Digital Versatile Disc, and MP3 players; digital and cellular telephones; digital cameras; TV and digital satellite; or wire and wireless networks. Medicinal devices would be less effective or incapable to ensure beneficial data in order to exact diagnoses if there were not any analyzers of digital Electrocardiography or digital x-rays and medicinal image systems. We would also live in many less effective methods, since we would not become accoutered with recognition of voice systems, systems of speech synthesis and systems of image and video editing. In the absence of Digital Signal Processing, engineers, scientists, and technologists would have not any strong apparatus to visualize and analyze information and build their design, and soon (Proakis & Manolakis, 2006).

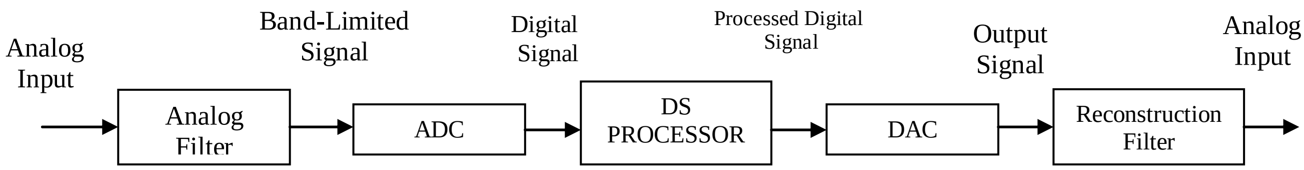


Figure 4.3: DSP regulation

Digital Signal Processing theory is defined by a simplified block diagram of Figure 4.3 that takes place an analog filter, an ADC unit, a processor of Digital Signal, a DAC unit, and a filter of reconstruction. As indicated diagram, analog input signal, that is continuous in time and amplitude, is usually met in our actual life. Examples of like these analog signals contain current, temperature, light intensity, pressure, and voltage. Normally a sensor is utilized to transform nonelectrical signal to analog electrical signal (voltage). This analog signal is fed to an analog filter that is implemented to restrict frequency analog signals domain previous to process of sampling. Filtration aim is to substantially reduce distortion of aliasing. Band-restricted signal at analog filter output is then sampled and transformed over Analog to Digital Converter unit into digital signal that is discrete both in amplitude and in period. Processor of Digital Signal then adopts processes digital information and digital signal accordingly, Digital Signal Processing rules like low pass, high pass, and band pass filtering of digital, or other algorithms in order to various implementations.

Attention which processor of Digital Signal unit is a private digital computer type and can be a generic goal a microprocessor, digital computer, or an advanced microcontroller; additionally, Digital Signal Processing rules can be applied utilizing software generally. With processor of Digital Signal and suitable software, a processed digital output signal is created. This signal proceeds in a way by certain algorithm utilized. Following diagram in Figure 4.3, DAC unit, transforms processing of digital signal for an analog output signal. As indicated, signal is discrete in amplitude and continuous in time the final diagram in Figure 4.3 is assigned as a function to smooth the Digital to Analog Converter output voltage levels back to analog signal over a restoration filter in order to actual world implementations. Generally, analog signal continuum does not need software, an algorithm, ADC, and DAC. Processing believes completely on electrical and electronic apparatus like transistors, resistors, operational amplifiers, capacitors, and Integrated Circuits(IC). Digital Signal Processing systems, but, utilize software, digital processing, and algorithms; so they have an excellent agreement of resilience, less noise attempt, and no signal distortion in different implementations. But, as illustrated in Figure 4.3, Digital Signal Processing systems still need minimum analog processing like anti-aliasing and restoration filters that are must in order to convert actual-world data into digital format and digital format back into actual world data. There are a lot of actual world Digital Signal Processing implementations which do not need Digital to Analog Converter, like information acquisition and digital data monitor, recognition of speech, information encoding, and so on. Likewise, Digital Signal Processing implementations which require no Analog to Digital Converter contain Compact Disc players, text-to-speech synthesis, and digital tone generators, among others (Vaseghi**,** 2009).

4.7 DSP Implementations

Implementations of Digital Signal Processing are ascending in a lot of fields where analog electronics are being changed by chips of Digital Signal Processing, and new implementations are depending on Digital Signal Processing methods. With of processors of Digital Signal cost decreasing and their performance increasing, Digital Signal Processing will proceed to impress design of engineering in our modern daily life. Some implementation samples utilizing Digital Signal Processing are given in Table 4.1. But, list in table by no means lids entire Digital Signal Processing implementations. Much more fields are ever being discovered by engineers and scientists. Implementations of Digital

Signal Processing methods will proceed to have deep effects and develop our lives (Tan & Jiang, 2013).

Table 4.1: Implementations of DSP

Digital Audio and Speech	• Digital Audio coding as Compact Disc players • Digital crossover • Digital audio equalizers • Digital stereo and surround sound, • Noise decreasing systems, • Speech Coding, • Data Compression, and encryption • Speech Synthesis and Speech Recognition.
Digital Telephone	• Speech Recognition • High-speed modems, • Echo deletion, • Speech synthesizers, • DTMF (dual-tone multi frequency) manufacture and detection • Answering machines.
Automobile Industry	• Actual noise control systems • Actual suspension systems • Digital audio and radio • Digital controls.
Electronic communications	• Cellular phones, • Digital telecommunications, • Wireless LAN(Local Area Networking), • Satellite Communications
Medical Imaging Equipment	• Electrocardiogram Analyzers, • Cardiac monitoring, • Medical imaging and recognition, • Digital x-rays, • Image processing.
Multimedia	• Internet phones, • Audio and video; hard disk drive electronics; digital pictures, • Digital cameras; • Text-to-voice and voice-to-text technologies.

4.8 Summary

In this section we have initiatived to ensure the motivation for digital signal processing as an alternate to analog signal processing. We described the necessary procedures can be used to convert an analog signal into a digital signal for processing and presents the basic components of a DSP system.

CHAPTER 5
BIOMEDICAL SIGNAL PROCESSING

5.1 Overview

Purpose of Biomedical Signal Processing is, to remove:

- Clinical
- Biochemical
- Pharmaceutical

appropriate data for enable a transmitted medicinal diagnosis. Whole living things, from cells to structure, transmit biological signals origin. These signals types can be

- Electrical Signal
- Mechanical Signal
- Chemical Signal

Entire these signals can be for diagnosis interest, in order to patient observing and biomedical exploratory. Primary biomedical signals duty processing for filtering signal of interest out of from noisy background and for decreasing unnecessary information stream to just several, however appropriate coefficients.

5.2 Properties of Medical Data

Alphanumeric data contain patient’s name and address, identity number, lab tests outcomes, and physicians’ annotations. Figure 5.1 shows three basic data types that must be acquired, manipulated, and archived in the hospital. Images contain x-rays and scans from computer tomography, magnetic resonance imaging, and ultrasound. of Physiological signals examples are ECG, Electroencephalogram, and blood pressure pursuiting. Quite dissimilar systems are necessary to manage each of these three kinds of information. Alphanumeric information are usually administrated and arranged into a database utilizing a general-objective mainframe computer. Image data are traditionally archived on film. However, we are evolving toward Picture Archiving and Communication Systems which will store images in digitized form on optical disks and deploy them on demand over a high-speed Local Area Network to very high resolution graphics display monitors located throughout a hospital. On the other hand, physiological signals like those that are monitored during surgery in the operating room require real-time processing. The clinician must know immediately if the instrument finds abnormal readings as it analyzes the continuous data (Tompkins, 2000).

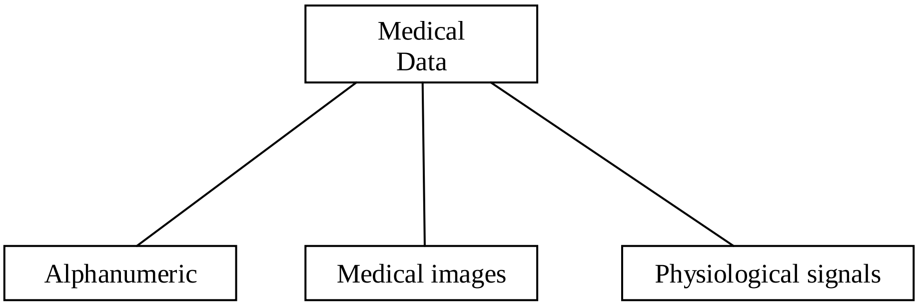


Figure 5.1: Types of medical data

5.3 What is a Medical Device?

There are many different types of medical instruments. Figure 5.2 indicates a block diagram which describes these kinds of instruments. Sensors measure the patient's physiological signals and generate electrical signals (usually time-varying voltages) which are analogs of the real signals. A set of electrodes may be used to sense a potential difference on the body surface such as an ECG or EEG. Sensors of different types are available to transduce into voltages such variables as body core temperature and arterial blood pressure. The electrical signals manufactured by the sensors interface to a processor that is liable for processing and analysis of the signals. The processor block typically contains a microprocessor for performing the necessary tasks. Many devices have the capability to monitor, register, or deploy through a network either the raw signal captured by the processor or the results of its analysis. In some devices, the processor implements a control function. Based on the outcomes of signal analysis, the processor might teach a controller to do direct therapeutic intervention on a patient or it may signal a person which there is a difficulty which is necessary feasible human intervention (open loop control).

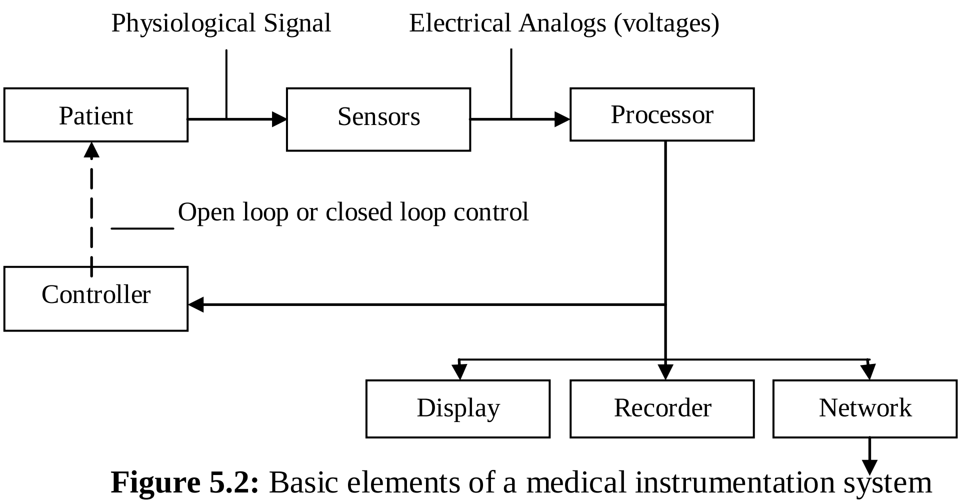


Figure 5.2: Basic elements of a medical instrumentation system

5.4 Iterative Definition of Medicine

The clinician inquires the patient questions about medical history, registers the Electrocardiogram, and does blood tests and other tests for describe the patient's problem. Figure 5.3 is a block diagram that shows the operation of the medical care system. Information collection is the starting point in health care. Of course medical instruments help in some aspects of this data collection process and even do some preprocessing of the data. Ultimately, the clinician analyzes the data collected and decides what the basis of the patient's problem is. This decision or diagnosis leads the clinician to prescribe a therapy. Once the therapy is administered to the patient, the process continues around the closed loop in the figure with more data collection and analysis until the patient's problem is gone (Ibrahimy, 2010).

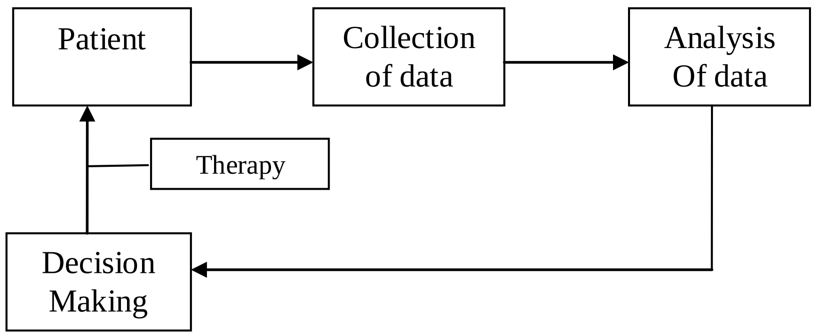


Figure 5.3: Fundamental components of a medical care system

5.5 Synopsis for Biomedical Signal Processing

Biomedical Signal Processing is mostly regarding innovative signal processing implementations techniques in signals of biomedical through different inventive combining of technique information of biomedical. It is a quickly increase in size area with a broad implementations range. These range from factitious limbs structures and assistances for disabled to advanced medical growth observing systems which can manage in a noninvasive attitude to give actual time workings body of human appearance. There are a number of medical systems in widespread utilize. These contains ultrasound; electrocardiography and plythesmography are broadly utilized a lot of objectives.

Biomedical signals processing generally includes of at least four stages:

- Measuring or investigation, which is, acquisition of signals.
- Transmutation and decline of signals.
- Coefficients of signal calculation which are diagnostically important.
- Explication or grading of signals

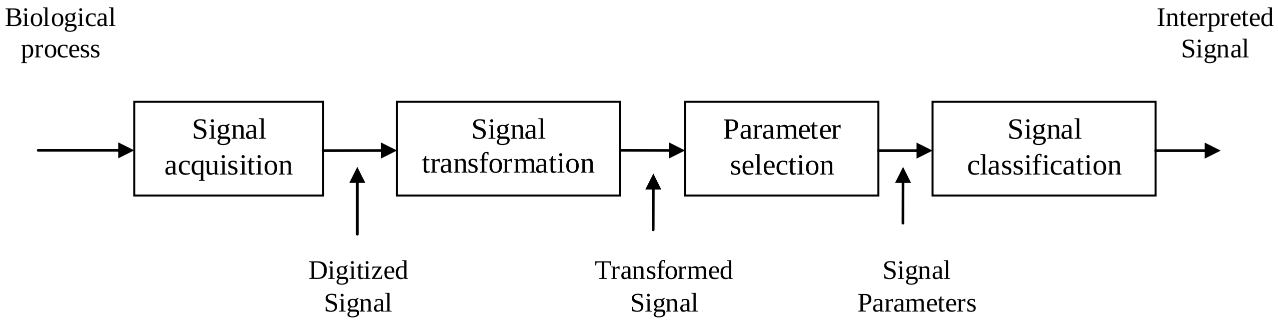


Figure 5.4: Biosignal processing phases

Types of biological signals into two main groups: stochastic (or statistical) and deterministic signals. Like a respiration or beating cardiac creates signals which are further recurrent. Deterministic category is subdivided into periodic, transient and quasiperiodic signals. Stochastic signals are subdivided into stationary and non-stationary signals. Cells categories depolarize in an approximately indiscriminate fashion like cells of muscle creating nerve cells or electromyography in cortex. Time varying signal wave figures are illustrated in Figure 5.5.

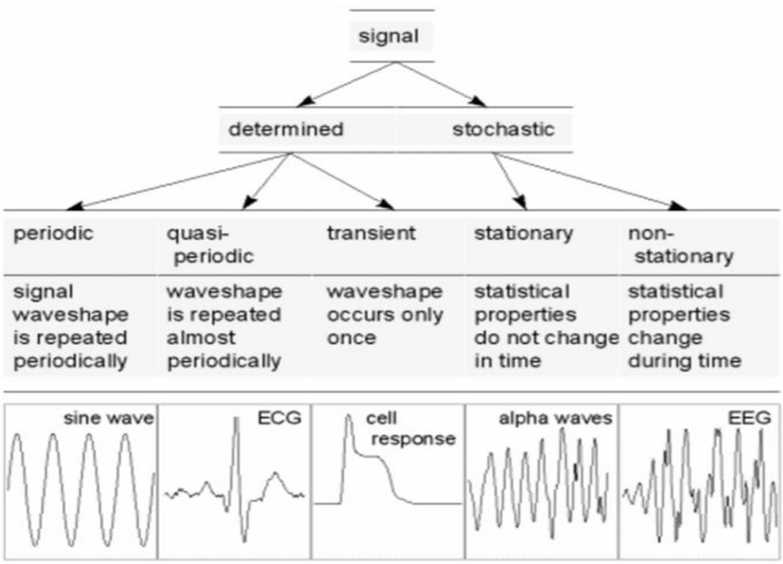


Figure 5.5: Forms of signal wave (Tompkins, 2000).

5.5.1 Obtaining of Biosignals

Actual-time obtaining of information directly from source by direct electrical connections to devices forestalls requirement for people to measure, encode, and enter information manually. Sensors annexed to a patient transform signals of biomedical, such as blood pressure, pulse ratio, mechanical motion, and electric action, for instance, of heart, muscle and brain, into electric signals, that are transferred to computer. Signals are exemplified periodically and are transformed to digital statetement in order to storage and processing. Automated information obtaining and processing of signal methods are especially significant in patient observing settings.

5.5.2 Digitization of Biosignals

Sampling and Quantization most inherently taking shape signals are analogue signals, so signals which change continually. Digital computer stores and processes values in discrete units. Prior to transaction is feasible, analogue signals must be transformed to discrete units. Transformation stage is named Analogue to Digital Conversion (ADC). Analog to Digital Converter can be considered as sampling and rounding; continuous amount is monitored at constant spacing and rounded to closest discrete unit. Two coefficients describe how intimately digital information encounters original analogue signal: sensitive with that signal is saved and frequency with that signal is sampled. Certainty defines sample accuracy degree investigation of a signal. It is defined by number of bits (quantization) utilized to symbolized a signal and their accuracy; more bits, levels greater number which can be separated. Certainty further is restricted by device correctness which transforms and transmits signal.

Ranging and devices adjustment, either manually or automatically, is essential for signals to become symbolized with as much certainty as feasible. Incorrect ranging will outcome in data bereavement. For instance, an alter in a signal which changes among [0.1V - 0.2V] will be undetectable if device has became adjust to register replaces among [0.0V - 1.0V] in 0.25 V steps. Sampling ratio is second coefficient which impresses communication among an analogue signal and its representation of digital. A sampling ratio which is very low notional to ratio at that a signal alterations value will manufacture a weak presentation. However, oversampling increases processing outgoing and storing information.

As a generic regulation, we require to sample at least twice as often as component of highest-frequency required from a signal. For example, looking at an Electrocardiogram, we find which prime iteration frequency is at most several per second, however which QRS complex includes a beneficial frequency component on 150 Hz layout. Therefore, information sampling ratio should be at least 300 measurements per second. This ratio is named Nyquist frequency.

5.5.3 Noise

Another signal view standard is noise quantity in signal, component of obtained information which is not owing to certain phenomenon being measured. A fundamental noise source is signals of electric or magnetic manufactured by nearby apparatus and power lines. Furthermore, mistakes in sensors, weak communication among sensor and source (patient), and inconvenience from signals manufactured by processes of physiological other than one being studied (for instance; respiration interferes with Electrocardiogram recording) are another widespread noise sources.

Property of noise is its relatively haphazard model in most situations. Filtering algorithms can be utilized to decrease noise effect. Recurrent signals, as an Electrocardiogram, can be integrated over different cycles, so decreasing haphazard noise effects. When noise model differs from signal model, Fourier analysis can be utilized to filter signal in domain of frequency.

5.5.4 Certainty and Correctness

Certainty mentions to measurement correctness; if measurement is recurred on same issue, same outcome will be got. Correctness mentions to propensity of measured worth to be symmetrically categorized around variant's actual worth. Medical information uncertainty can originate from “intra” and “inter” instrumental and observer variations (analytical or metrological uncertainty) or “intra” and “inter” single variations (biological uncertainty); is a combination of all of them.

5.5.5 Abstraction and Analysis

Formerly datum have became achieved and filtered, they typically are processed to decrease their volume and to abstract knowledge in order to utilize by explication programs. Frequently information is examined to remove significant coefficients, or, signal properties, e.g., period or Electrocardiogram ST segment intensity. Computer can also investigate and categorize waveform figure by comparing signal to acknowledged models. Upward analysis (in conjunction with the appropriate knowledge base) is essential to define meaning or signals significance e.g., to let automated Electrocardiogram-based cardiac diagnosis.

5.6 Summary

Biomedical signal processing is a quickly growing area with an extensive implementations range. These range from building limbs factitious and help for disabled to advanced medical imaging systems improving which can utilize in a non-invasive style to give actual functioning human body time views.

CHAPTER 6

DIGITAL FILTERING & NOISE TYPES

6.1 Overview

Processing of digital signal affords major resilience, higher performance (in terms of attenuation and selectivity), preferable duration and surroundings stability and nominal device manufacture prices than conventional analog methods.

Discrete-time, discrete-amplitude convolver merely is digital filter. Fundamental theory of Fourier transform defines which two series linear convolution in time domain is same with two suitable spectral series multiplication in frequency domain. Filtering is in principle signal spectrum multiplication by filter frequency domain impulse response.

6.2 Signals and Data

A signal is quantity change by that data is transmitted regarding case, properties, composition, trajectory, evolution, and behavior or data source objective. A signal is transmitting data concerning means case(s) of a variable. Data transmitted in a signal may become utilized for communication, decision-making, control, geophysical exploration, forecasting, forensics, medicinal diagnosis, etc. by humans or machines. Types of signal which processing of signal deals with contain;

- Medical
- Ultrasonic
- Image
- Biological
- Audio
- Subsonic
- Financial
- Textual data
- Seismic signals.
- Electromagnetic

Figure 6.1 describes a system of communication created of a data resource, I(t), pursued by a system, T[.], in order to data transmutation into signal variation, x(t), a channel of communication h[.], for signal spread from transmitter to receiver, additive channel noise, n(t), and a processing of signal unit at receiver for subtraction of data from received signal. Generally, there is a mapping process which maps output, I(t), of an data resource to signal, x(t), which transports data; this mapping operator may be indicated as T[.] and represented as equation 6.1 given below:

$$x(t)=T^{*}[I(t)] \tag{6.1}$$

Last few decades, theory and processing of digital signal implementations have developed to play a centric role in contemporary telecommunication growth and data technology systems. Processing of signal techniques are centric to effective communication, and to smart man–machine interfaces progress in fields like speech and recognition of visual pattern for multimedia systems. Generally, DSP is related with two wide fields of data theory:

- Effective and dependable signals storage, transmission, reception, coding and representation in communication systems;
- Data Subtraction from noisy signals for recognition of pattern, forecasting, decision-making, detection, enhancement of signal, control, automation, etc.

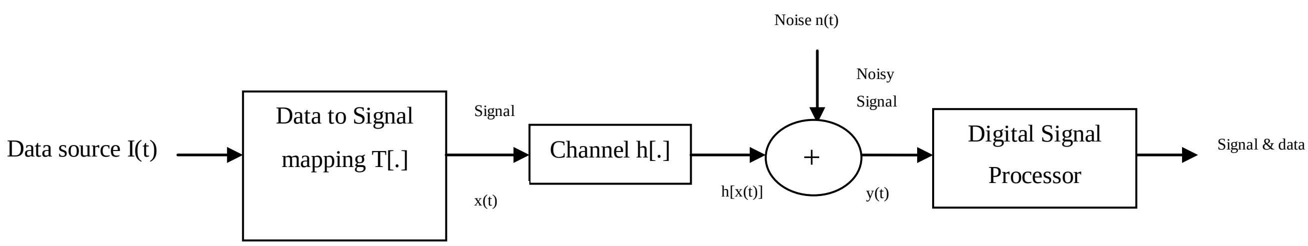


Figure 6.1: Communications and signal processing system statement

6.3 Implementations of DSP

In recent years, growth and commercial presence of increasingly strong and purchasable digital computers has became participated by advanced DSP algorithms progress for a wide variety of implementations like noise decrease, sonar, video, telecommunications, radar and signal processing of audio signal, recognition of pattern, geophysics explorations, forecasting of data, and large processing of database for subtraction, identification and obscured underlying constructions organization and models.

6.4 Noise and Distortion

An undesirable signal which interferes with communication or other signal measurement can become described as Noise. A noise itself is a signal which transmits data concerning noise source. For instance, noise from a car engine transmits data concerning case of engine and how smoothly it is working. Noise resources are many and changed and contain noise of thermal real to electrical conductors, shot racket natural in flows of electric current, audio periodicity acoustic racket emanating from vibrating, moving or colliding resources like returning engines, moving tools, rain, computer fans, wind, keyboard clicks, etc. and radio periodicity noise of electromagnetic which can interfere with voice transfer and receiving, image and information over spectrum of radio-frequency. Signal distortion is locution frequently utilized to define a systematical unwanted modify in a signal and applies to modifies in a signal because of not ideal communication channel features, reverberations, echo, reflections of multipath and deficient exemplaries. Primary factors restricting transmission of data capability in telecommunications and accuracy in systems of signal measurement are noise and distortion. That’s why modeling and noise elimination effects and distortions have became at core of theorem and communications application and processing of signal. Noise separation and distortion elimination are significant issues in implementations like cellular mobile communications, recognition of speech, processing of image, signal processing of medical signal, sonar, and radar in any implementation where signs cannot become reserved from racket and distortion (Intersil, 1999).

6.5 Noise Types

Any undesirable signal which interferes with communication, measurement, perception or data-bearing processing of signal may become described as Noise. In different degrees in nearly whole environments Noise is available. Noise can reason errors of transmission and may moreover disturb a communication process; therefore processing of noise is a significant and modern integral part telecommunications and systems of signal processing.
Noise processing technique achievement depends on its capability to define pattern noise continuum, and to utilize noise properties favorable to distinguish signal from racket. Depending on its resource, a racket can become categorized into a number of classes, demonstrating noise wide physical nature, given below:

Acoustic noise

Infiltrates from vibrating, moving, or colliding resources and is best known noise kind available to different degrees in regular surroundings. Acoustic racket is created by this kind of resources like traffic, people talking in background, computer fans, air-conditioners, moving cars, rain, wind, etc.

Thermal noise and shot noise

Noise of thermal is created by haphazard thermally energized particles movements in an electric conductor. Noise of thermal is real to whole conductors and is available without any implemented voltage. Shot racket occurs electric current random fluctuations in an electrical conductor and is real to current flow. Shot racket is caused by truth which current is transported by discrete charges (i.e. electrons) with haphazard surges and times of random arrival.

Electromagnetic noise

Electromagnetic noise is available entire periodicities and in specific at radio periodicity range (kHz to GHz range) where telecommunications occurred. Whole electric apparatuses, like radio and television transmitters and receivers, create noise of electromagnetic.

Electrostatic noise

Created by voltage asset together or separately current flow. Lighting of fluorescent is one of more widespread electrostatic noise resources.

Channel distortions, echo and fading

Owing to not ideal communication channels properties. Channels of radio, like those at GHz periodicities utilized by operators of cellular mobile phone, are especially responsive to spread channel environment properties and signals fading.

Processing noise

Noise which outcomes from signals digital to analogue processing, e.g. quantization racket in numerical speech coding or image signals, or missing information packets in systems of digital data communication.

Depending on its periodicity spectrum or duration properties, a noise continuum can become additionally categorized into one of different classes given below:

White noise

Simply haphazard noise which has a flat spectrum of power. White racket in theoritical includes entire frequencies in tantamount density.

Band-restricted white noise

A racket with a flat spectrum and a restricted bandwidth which generally lids restricted apparatus spectrum or sign of interest.

Narrowband noise

Racket processes with a limited bandwidth like a 50–60 Hz ‘hum’ from electricity provide.

Colorful noise

Nonwhite racket or any broadband racket whose spectrum has a nonflat form; examples are brown racket, pink racket and autoregressive racket.

Impulsive noise

Includes short-period haphazard amplitude pulses and haphazard time.

Transient noise pulses

Includes comparatively lengthy time pulses of noise.

6.6 How Data is indicated in Signals?

Most significant part of any Digital Signal Processing duty understands how data is included in signs you are working with. There are a lot of ways which data can become included in a sign. If signal is manmade this is particularly true. Fortunately, there are just two paths which are common for data to become symbolized in inherently consisting signals.

- Data symbolized in time domain
- Data symbolized in frequency domain.

Data symbolized in time domain defines when something comprises and what magnitude of event is. For instance, imagine an essay to study light outcome from sun. Light outcome is measured and registered once each second. Every exemplary in sign demonstrates what is occurrence at that moment, and level of event. If a solar flare takes shape, sign directly ensures data on time it took place, period, growth over time, etc. Every sample includes data which is interpretable without reference to any other exemplary. Even though you have only one exemplary from this sign, you still know something about what you are measuring. This is basic method for data to become included in a sign. Backwards, data symbolized in frequency region is more indirect. A lot of things in our universe indicate periodical movement. For instance, a wine glass struck with a fingernail will vibrate, producing a ringing sound; pendulum of a grandfather clock swings back and forth; stars and planets rotate on their axis and return around each other, and so forth. By measuring periodic periodicity, phase, and magnitude movement, data can frequently be got about system producing movement. Presume we exemplary sound manufactured by ringing wine glass. Basic periodic vibration periodicity and harmonics belong to mass and elasticity of material. A single exemplary, in itself, includes no data about periodical movement and for this reason no data about wine glass. Data is included in relationship among a lot of points in signal.

6.7 Filtering of Signals

Filtering of signal is frequently utilized in testing of eddy current to clear undesirable periodicities from receiver signal. While settings of correct filter can significantly develop a defect signal visibility, inaccurate arrangements can distort presentation of signal and even clear flaw signal fully. For this reason, it is significant to understand filtering of signal notion. Filtration is applied to receive signal and, for this reason, is not directly concerned to probe drive periodicity. This is most easily understood when picturing a time versus signal amplitude screen. With this screen mode, it is easy to see which signal form is dependent on time or period which probe coil perceives something. For instance, if a surface probe is established on conductor surface and rocked back and forth, it will propagate a wave like signal. When probe is rocked fast, signal will have a higher periodicity than when probe is rocked slowly back and forth.

Signal does not need a wavelike view to have periodicity content and most eddy current signals will be created of a large number of periodicities.

6.8 Digital Filtering Fundamental Notions

Digital filtering has certain properties which you require to pay private attention to. Analog input sign must fulfill specific necessities. Additionally, on converting an output digital sign into analog form, it is necessary to implement processing of additional signal for get the suitable result. Figure 6.2 illustrates digital filtering process block diagram.

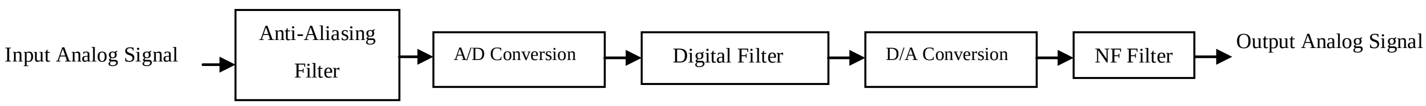


Figure 6.2: Digital filtering process

Transforming an analog signal into digital form process is applied by sampling with a finite sampling periodicity "f_s". If an input sign includes periodicity components higher than half sampling periodicity ($f_s/2$), it will reason distortion to original spectrum. This is cause why it is first necessary to apply filtration of an input sign utilizing a low-pass filter which clears high periodicity components from input periodicity spectrum. This filter is known anti-aliasing filter as it forestalls aliasing.

After filtering and sampling method, a digital signal is available in order to upward processing that, in this case, is filtration utilizing suitable digital filter. Output signal is also a digital signal that, in some cases, is necessary to become transformed back into analog form. After Digital to Analog Conversion, signal includes some periodicity components higher than $f_s/2$ that must become cleared.

6.9 Types of Digital Filters

Filter is a system that passes specific frequency components and completely refuses all others, but in a broader status any system which changes specific frequencies relative to others is named a filter.

Digital filters are used for two generic aims:

- Signals Segregation which have been combined.
- Signals Renovation which have became damaged somehow.

Analog (electronic) filters can become utilized for these same duties; but, far excellent outcomes can be achieved by digital filters. Digital filters are a very significant part of Digital Signal Processing. Actually, their exceptional performance is one of the key causes which Digital Signal Processing has been very popular, filters have two utilizes:

- Segregation of Signal
- Renovation of Signal

Segregation of signal is necessary when a signal has became corrupted with attempt, racket, or other signals. For instance, imagine an apparatus in order to measuring electrical baby's cardiac action (ECG) while still in womb. Raw sign will likely be disturbed by breathing and mother heartbeat.

A filtrate might be utilized to separate these signs so which they can be individually analyzed. Renovation of signal is utilized when a sign has became damaged in somehow. For instance, an audio registering made with weak device may become filtrated to

preferable symbolize sound as it in fact occurred. Another example is of an image deblurring obtained with an incorrectly focused lens, or a shaky camera.
These problems can become attacked with either analog or digital filtrates. If we compare these filters, analog filtrates are inexpensive, fast, and have a large dynamic range in both magnitude and periodicity. Numerical filtrates, in comparison, are much superior in performance level which can become accomplished.

There are two fundamental digital filters types:

- Response of finite impulse
- Response of infinite impulse

Generic form of digital filter difference equation is:

$$y(n) = \sum_{i=0}^{N} a_i x(n-1) - \sum_{i=1}^{N} b_i y(n-i) \tag{6.2}$$

where current filter output is “y(n)”, past filter outputs are “y(n-i)” ’s, current or past filter inputs are “x(n-i)” ’s, filter’s feed forward parameters corresponding to filter zeros are “a_i“’s, filter’s feedback parameters suitable to filter poles are “b_i” ’s and filter’s order is “N”. Infinite impulse response filters have one or more nonzero feedback parameters. This is, as feedback term outcome, if filter has one or more poles, once filter has been induced with an impulse there is always an output. Finite Impulse Response filtrates have no non-zero feedback parameter. Which is, filtrate has only zeros, and once it has became induced with an impulse, outcome is available for only a finite (N) number of computational cycles.

6.10 Summary

One of strong devices of Digital Signal Processing is Digital filtration. Except clear essentially clearing errors advantages in filtrate associated with passive component surges over time and temperature, op amp drift (active filters), etc., numerical filtrates are talented performance descriptions which would, at best, become highly hard, if not unfeasible, to attain with an analog application. Furthermore, digital filtrate properties can become easily changed under software control.

For this reason, they are widely utilized in adaptive filtration implementations in communications like cancellation of echo in modems, noise extraction, and recognition of speech.

In processing of signal, function of a filter is to eliminate undesirable signal parts, like haphazard noise, or to remove beneficial signal parts, like components lying within a specific range of frequency.

CHAPTER 7
EXPERIMENTAL OUTCOMES

7.1 Overview

Neonatal healthcare is always associated with fetus health as if any conditions can be diagnosed, and then there are maximum chances that the condition can be treated before the birth. Diagnosing any pathological condition during pregnancy normally asphyxia is very important. Electrocardiogram or called as ECG is one of the simplest and painless noninvasive diagnosis method to estimate the heart condition Fetal ECG (FECG) signal provides valuable information of the fetus physiological state, this is acquired by placing skin electrodes on mother's abdomen. As ECG is measuring the electrical activity, ECG from the abdomen (AECG) is usually corrupted or has interferences which basically can be categorized as noise in the course of a cardiac cycle Electrocardiogram signal composed of P, QRS, and T wave. Detecting R peak from QRS complex from abdominal ECG is very important. ECG for an adult is measured from chest, so considering this maternal ECG can be obtained from chest which would not have Fetal ECG.Various researchers have put forward the technique of extracting Fetal ECG by taking maternal ECG from two location chest and abdomen .The abdominal signal is a compound signal of Fetal Electrocardiogram and maternal Electrocardiogram whereas chest lead signal consist of only maternal ECG. Various techniques have been proposed by researchers such as:

- Wavelet filtering
- Correlation technique
- Filtering technique

Noise canceller needs a reference signal which is given in the form of maternal electrocardiogram signal. To understand how it works every heartbeat is an electrical signal which spreads from the chest to the bottom, and process repeats where the signal set a rhythm which can be seen as a heartbeat.

7.2 Methodology

The signal is acquired from physionet database (Ruha & Nissila, 1997). Were we have two sets of signal first set contains signal from mothers abdomen consisting of fetal ECG, maternal ECG and noise. In second set we have maternal ECG taken from the mother's chest. Heartbeat of fetus is noticeably higher than mother ranging till 160 beats per minute.

Fetal ECG amplitude is feeble than which of the maternal which corresponds to 0.25 millivolts peak voltage.

Composing Maternal Heart Beat Signal

In this part, Electrocardiogram forms will be simulated for both the mother and fetus. 4 kHz sampling rate will be used. Heart rate for this signal is roundly 89 bpm, and 3.5 mV peak voltage signal.

Measured Maternal Electrocardiogram

Maternal ECG signal is got from mother chest. Adaptive noise cancellation aim in this study is to adaptively extract maternal heartbeat signal from fetal ECG signal. Canceller requires a reference signal created from a maternal ECG to carry out this work. Just as fetal ECG signal, maternal ECG signal will include some additive wideband noise.

Composing Fetal Heart Beat Signal

Fetus beats heart recognizably faster than which of its mother, with ratios ranging from 120 to 160 bpm. Fetal ECG amplitude is also very feeble than which of maternal ECG. Sample creates an ECG signal suitable to a heart rate of approximately 139 bpm and 0.25 mV peak voltage for simulating fetal heartbeat.

Measured Fetal Electrocardiogram

Measured fetal ECG signal from mother abdomen is generally predominated by maternal heartbeat signal which radiates from chest cavity to abdomen. This radiation will be defined as path as a linear Finite Impulse Response filter with 10 pitched on parameters. Additionally, it will be added a small uncorrelated Gaussian noise quantity to liken any wideband noise sources in measurement.

For extraction of maternal and fetal ECG we utilize Savitzky&Golay Filter and Adaptive Noise Canceller by the application of two signal an input and reference. Figure 7.1 demonstrates the overview of the methodology of the study.

Savitzky-Golay Filter is tried firstly with WGN and then Adaptive Noise Cancellation technique is implemented. PSNR value among real and de-noised signals are computed.

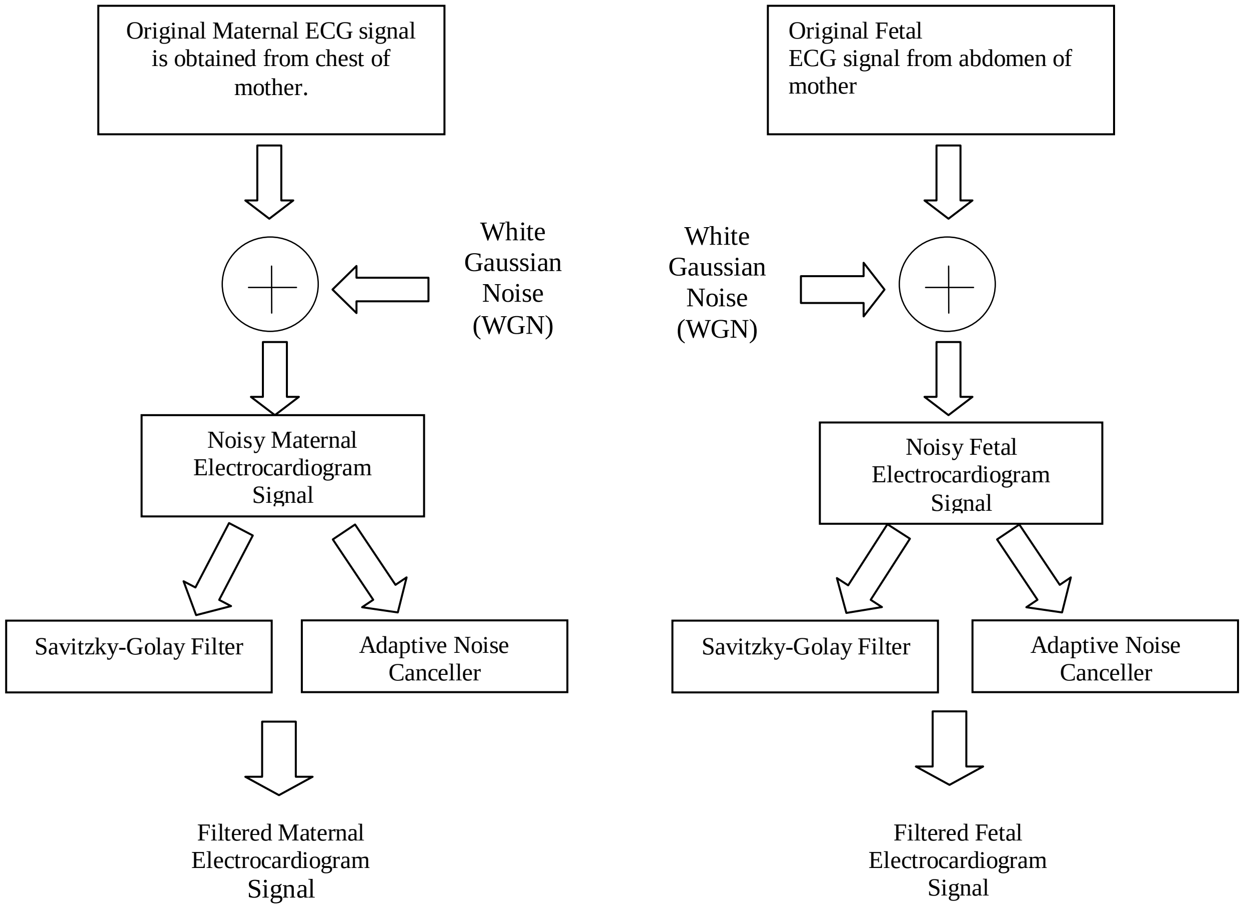


Figure 7.1: Overview of the complete system

Figure 7.1 indicates overview of the complete system designed for this study. Original Maternal ECG signal obtained from chest of mother and Original Fetal ECG signal obtained from abdomen of mother is acquired from Physionet database. The noisy Maternal and Fetal ECG signals have been composed by adding convenient noise distributions with reference signal. Savistsky-Golay Filter and Adaptive Noise Cancellation Least Mean Square(LMS) algorithm techniques are tested with White Gaussian noise (WGN) is applied.

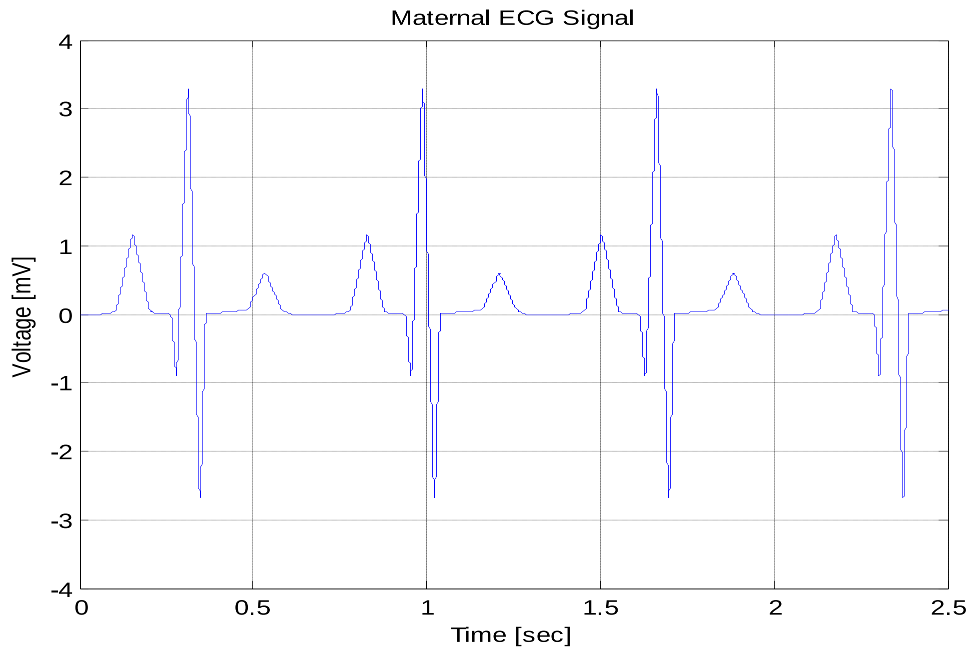


Figure 7.2: Representative noise free maternal electrocardiogram signal

Figure 7.2 and Figure 7.3 indicates Exemplary Noise Free maternal and Fetal Electrocardiogram signals respectively. Technical informations about these signals were explained above.

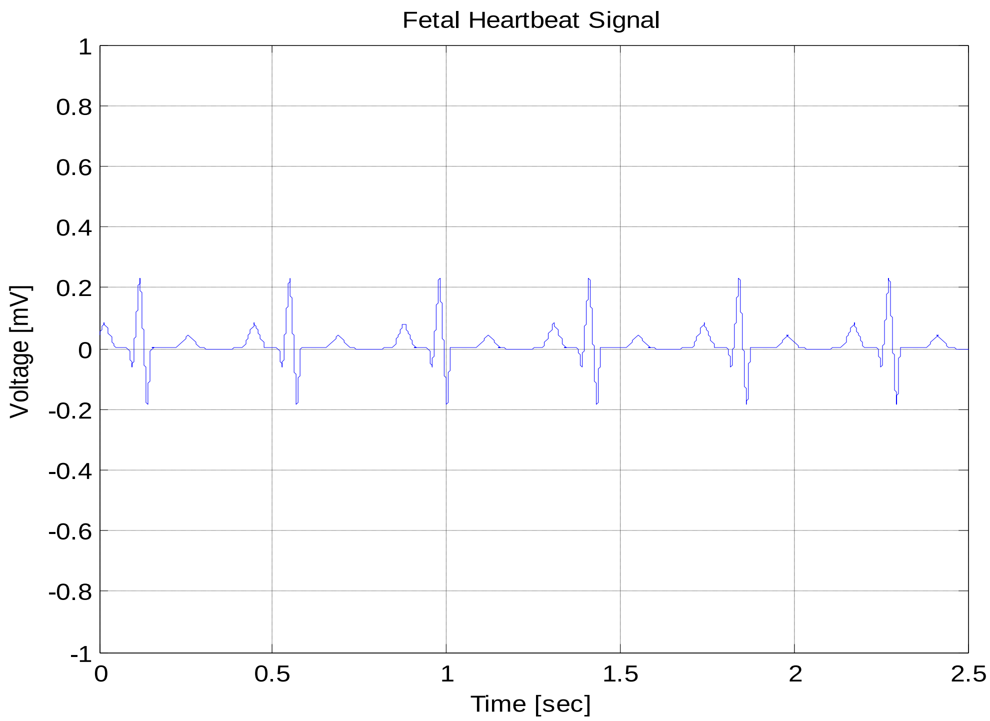


Figure 7.3: Representative noise free fetal electrocardiogram signal

Additive White Gaussian Noise

AWGN is a fundamental noise model utilized in data theory to mimic the influence of many random processes which take shape in nature. The modifiers indicate certain properties:

Additive: Because the noise will get added to your transferred signal not multiplied. Thus, received signal y(t) = x(t) + n(t), where x(t) was original clean transferred signal, and n(t) is the noise or discomfort in channel.

Gaussian: This thermal noise is haphazard in nature, certainly noise can't be deterministic else you would extract deterministic noise from y(t) as soon as possible you receive y(t). Thus, this random thermal noise has Gaussian distribution with “0” mean and variance as Noise power. “0” means which anticipated value n(t) during any time interval “T” is “0”. But merely put, it additionally means which on an average n(t) will take “0” value. And n(t)=0 probability is the highest and probability rapidly reduces as you increase the magnitude of n (t).

White: meaning same amount of all the colors. Or same power for all the frequencies. That means that this noise is equally present with the same power at all the frequencies. Thus, in frequency domain, Noise level is straight along at each frequency.

It's a straightforward imperfections model which communication channel consists of. When you transfer certain signal into space or atmosphere or copper line to be received at other end, there are disturbances (aka noise) present in channel (space/atmosphere/copper line) because of various causes. One such reason is the thermal noise by the virtue of electrons' movement in the electronic circuit being utilized for transmission and reception of signal. This disturbance or noise is modeled as Additive White Gaussian Noise.

7.3 De-noising of ECG Signal

Digital filtering methods can be utilized for develop signal quality and decrease haphazard error noise component [51]. If we think following equation:

$$y(t) = x(t) + n(t) \tag{7.1}$$

Where x(t) is real signal of maternal and fetal ECG measured signal at time t, n(t) is random noise affecting it, which is presumed to be additive and y(t) is the received signal from Electrocardiograph. One significant problem in low-pass filtering is which, since signal and noise spectra ordinarily overlap, it is not feasible to extract random noise n(t) from measured signal y(t) without distorting real signal x(t).The goal of this thesis is to present and define an method of Savitzky-Golay filter for de-noising of ECG signal. The Noisy ECG Signals have been created by adding the suitable noise dispersions with the reference signal. The Savitzky-Golay Filter is tested with WGN is applied. The PSNR rate among the real and de-noised signals are calculated.

7.4 Filtering Methods

In this part filtering techniques Savitzky-Golay Filter and Adaptive Noise Cancellation which is applied for this study will be defined.

7.4.1 Savitzky-Golay Filter

Savitzky-Golay smoothing filter was essentially introduced by Abraham Savitzky and Marcel J. E. Golay in 1964, in their paper “Smoothing and Differentation of information by Simplified Least Squares Procedures”. They established themselves frequently matching Noisy spectrum where simple noise-decrease processes, like running averages, only were not good sufficient for removing well-defined properties of spectral peaks. Particularly any running averaging incline to smooth and widening peaks in a spectrum and as the peak breadth is an significant coefficient when describing relaxation times in molecular systems, like this noise-decrease methods are openly non-attractive. The prime opinion introduced by Savitzky and Golay was a work-around forestall the issues matched with running averages, while stil protecting the smoothing of information and distribution protecting properties as relative maxima, minima and width. Savitzky and Golay suggested information smoothing technique based on local least-squares polynomial approximation. They indicated which fitting a polynomial to input set examples and then appraising resulting polynomial at a single point in approximation interval is equal to discrete convolution with a constant impulse response. Low pass filters got by this technique are widely known as Savitzky-Golay filters. Savitzky and Golay were interested in smoothing noisy information got from chemical spectra analyzers, and they indicated which least squares smoothing decreases noise while providing form and waveform peaks height (in their case, Gaussian shaped spectral peaks).This algorithm is a smoothing filter which actually implements a polynomial decline of a specific degree to a time-series. The benefit of the Savitzky-Golay filter is which it tends to protect specific properties of the time-series like local minima and maxima. The algorithm calculates a local polynomial decline on the input data by solving the equality:

$$Y = a_0 + a_1 z + a_2 z^2 + ... + a_k z^k \tag{7.2}$$

Savitzky-Golay smoothing and differentiation filter optimally complies information set points with a polynomial in least-squares sense. Savitzky and Golay have represented in their original paper which a moving polynomial fit can be numerically committed in completely the same path as a weighted moving average, since the parameters of the smoothing method are fixed for all “y” values (Savitzky & Golay, 1964). So, Savitzky-Golay smoothing is very simple to implement. Additionally, it can be indicated which the same algorithm can be utilized to compute smoothed first and second derivatives of the signal. In the classic article written by Savitzky and Golay that has been cited more than 3800 times accordingly Web of Science (ISI), digital filter type for smoothing and differentiation was improved. In their method, each sequential subset of “2m + 1” points is fitted by a polynomial of degree “n” (n $\leq$2m) in least-squares sense. The “s-th” (0$\leq$ s $\leq$ n) differentiation (zeroth differentiation= smoothing) of original information at midpoint is got by implementing differentiation on fitted polynomial instead of on original information. Eventually, running least-squares polynomial fitting can be implemented merely and automatically by convolving all input information with a digital filter of length “2m + 1”. History and growth of Savitzky–Golay smoothing and differentiation filter have been reviewed in shortly as;

$$G=S\,(S^T S)^{-1}= [g_0, g_1,\dots,g_n] \tag{7.3}$$

Matrix $G_{(2m)x(n+1)}$ includes convolution SG filter parameters for various order differentiation at origin (which is, imaginary midpoint or center of symmetry) specified by the smoothing and the differentiation expressions;

$$f_n(t) = \sum_{i=-m+1}^{m} h_{n,0,t,m,i} x_i \tag{7.4}$$

$$f_n^{(s)}(t) = \sum_{i=-m+1}^{m} h_{n,s,t,m,i} x_i \tag{7.5}$$

Severally where $f_n(t)$ and $f_n^{(s)}(t)$ are smoothing value and s-th$(1 \leq s \leq n)$differentiation value appraised at position “t”, with polynomial order “n” and information number “2m” ;

x_i is original information value at point "i " before shifting origin $(-m+1 \le i \le m)$; and $h_{n,0,t,m,i}$ and $h_{n,s,t,m,i}$ are appropriate parameters for smoothing and differentiation, separately.

There are 2 choices for coefficients:

- k - Degree of polynomial.
- f - Frame size.

Coefficients of Savitsky-Golay filter are the frame size and polynomial degree and all performance is addicted on these coefficients. The study and measurement noise variance are initialized for Savitzky-Golay Filter as a cubic Savitzky-Golay filter to information frames of length 41(k=3, f=41).

7.4.2 Adaptive Noise Cancellation

Adaptive Noise Cancellation is an alternate forecasting signals method distorted by additive noise or interference. Its benefit lies in which, with no possible signal or noise forecasts, noise levels refusal are attainable which would be hard or unfeasible to attain by other signal processing extracting noise techniques. Its cost, necessarily, is which it necessities two inputs a prime input including distorted signal and a reference input including noise accommodated in some obscure way with prime noise. Reference input is adaptively filtered and extracted from prime input to get signal forecast. Adaptive filtering before extraction authorizes inputs restorations which are deterministic or stochastic, stationary or time-variable. Uncorrelated noises effect in prime and reference inputs, and signal components asset in reference input on Adaptive Noise Canceller performance is researched. It is indicated which in uncorrelated noises failure and when reference is independent of signal, noise in prime input can be actually fulfilled without signal distortion.

Let "N" parameters of fitler at kth repetition be indicated as $W_k=[w_1(k), w_2(k),\dots, w_n(k)]^T$. For an input vector $X_k=[x(k), x(k-1), \dots x(k-n)]^T$ output will be given in next equation;

$$y(k) = \sum_{i=0}^{N} w_{\,i}(k)s(k-i) = w_{\,k}^{\,T} X_{\,k} \tag{7.6}$$

Filter's mission is to adjust its weights "W" iteratively to reduce Mean Square Error among primary and reference inputs. This regulation is primarily obtained by; Least Mean

Square, owing to significant Least Mean Square properties: simplicity and relatively fewer computational processes, it is positive in many implementations like unknown signals approximation. LMS weights adapting algorithm can be calculated at k^{th} repetition as in next equation:

$$W_{k+1}=W_k + \mu_k e(k) X_k \tag{7.7}$$

Where μ is step size coefficient that controls convergence ratio. Value of this step size should be optimized empirically to trade off convergence speed and indecision.

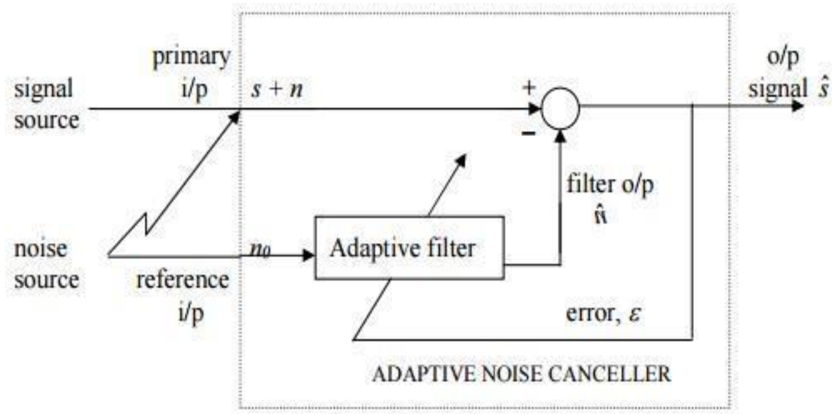


Figure 7.4: Adaptive noise cancellation

As illustrated in figure, an Adaptive Noise Cancellation has two inputs prime and reference. Prime input receives a signal "s "from signal source which is distorted by noise asset "n" uncorrelated with signal. Reference input gets a noise "n_0" uncorrelated with signal but correlated in some way with noise "n". Noise "n_0" goes through a filter to fabricate an output "ˆn" which is a close prime input noise forecast. This noise forecast is extracted from distorted signal to fabricate signal forecast at "sˆ", Adaptive Noise Canceller system output.

In noise deleting systems a practical target is to fabricate a system output "sˆ = s +n – n" which is a best fit in least squares sense to signal "s". This goal is achieved by feeding system output back to adaptive filter and tuning filter through a Least Mean Squares adaptive algorithm to reduce total system output power.

- *ha* = adaptfilt.lms(l,step,leakage,coeffs,states)
- *l:* Adaptive filter length (parameters number or taps) and it must be a positive whole number (defaults to 10)
- *Step:* LMS step size. It must be a nonnegative numerical. step defaults to 0.1.h you can utilize maxstep to specify a plausible step size range values for signals being processed. “hstep” defaults to 0.1.
- *Leakage:* Your LMS leakage factor. It must be a numerical between 0 and 1.When leakage is less than one, “adaptfilt.lms” applies a leaky Least Mran Squares algorithm. When you extract leakage feature in calling syntax, it defaults to 1 supplying no leakage in adapting algorithm.
- *Coeffs:* Primary filter vector parameters. It must be a length l vector. “Coeffs” defaults to length l vector with elements equal to zero.
- *States:* Vector of primary filter expresses for adaptive filter. It must be a length l-1 vector. States defaults to a length l-1 vector of zeros.

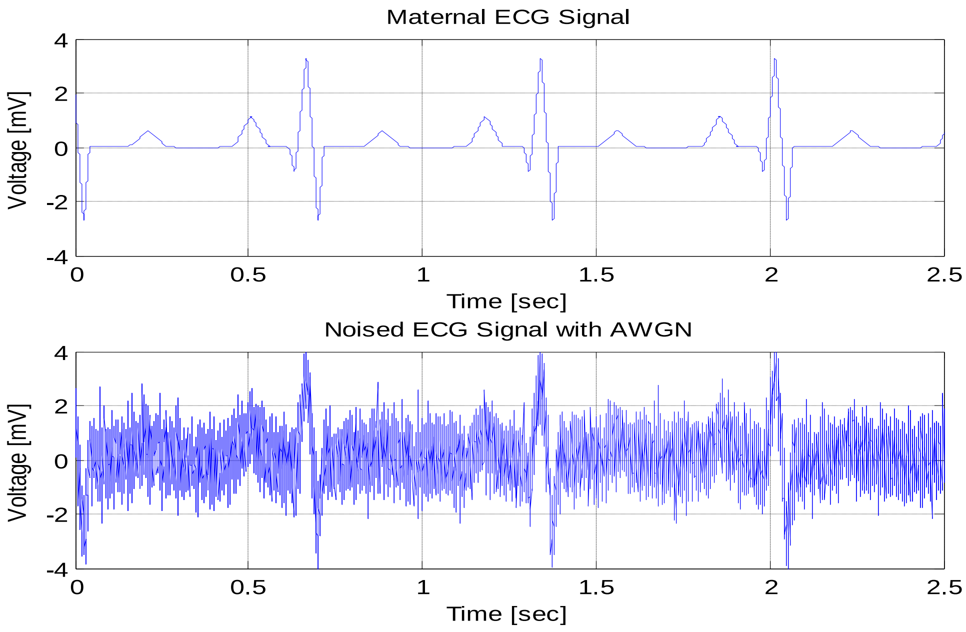
For this study Adaptive filter length is 15 and LMS step size is 0.001.

7.5 Results of Experiments (Savitzky&Golay Filter)

In this section the results obtained from Savitzky-Golay Filtering will be demonstrated.

The results shown below are given as a graph. Figures shows in order:

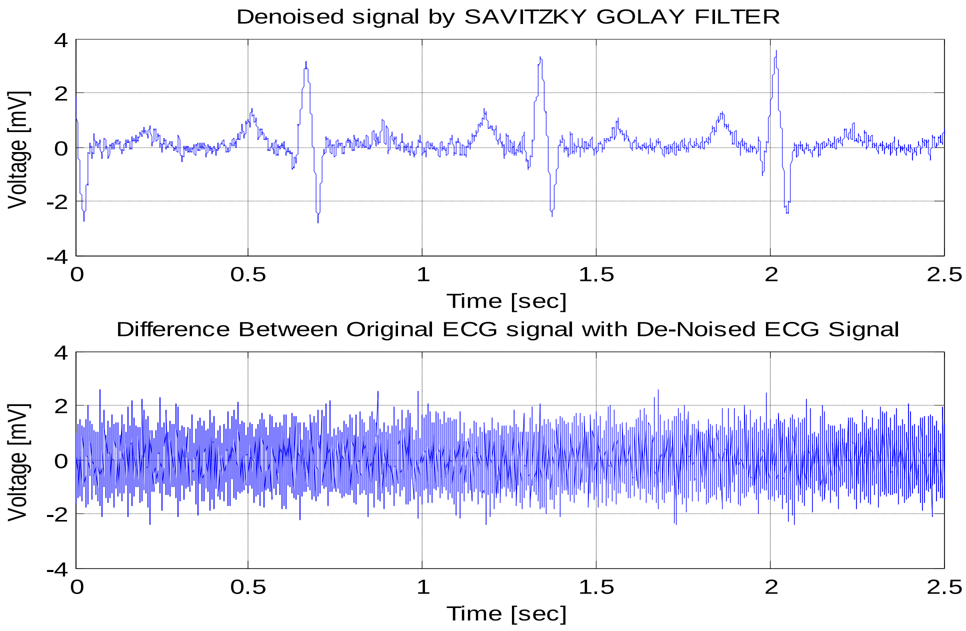
- Top Left graph shows created Original Maternal and Fetal ECG signals.
- Top Right graph shows noised, Maternal and Fetal ECG signals
  With various values of AWGN Noise.
- Bottom left graph shows De-noised ECG signals with Savitzky-Golay Filter.
- Bottom Right graph shows difference between Original ECG signal with De-Noised ECG Signal.



(a)

(b)

Figure 7.5 (a) and (b) indicates Original Maternal ECG signal and noised Maternal ECG signal by Additive White Gaussian Noise with SNR=0 dB.



(c)

(d)

Figure 7.5: Maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=0 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.5 (c) and (d) shows Denoised Maternal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Maternal ECG signal with de-noised ECG signal.

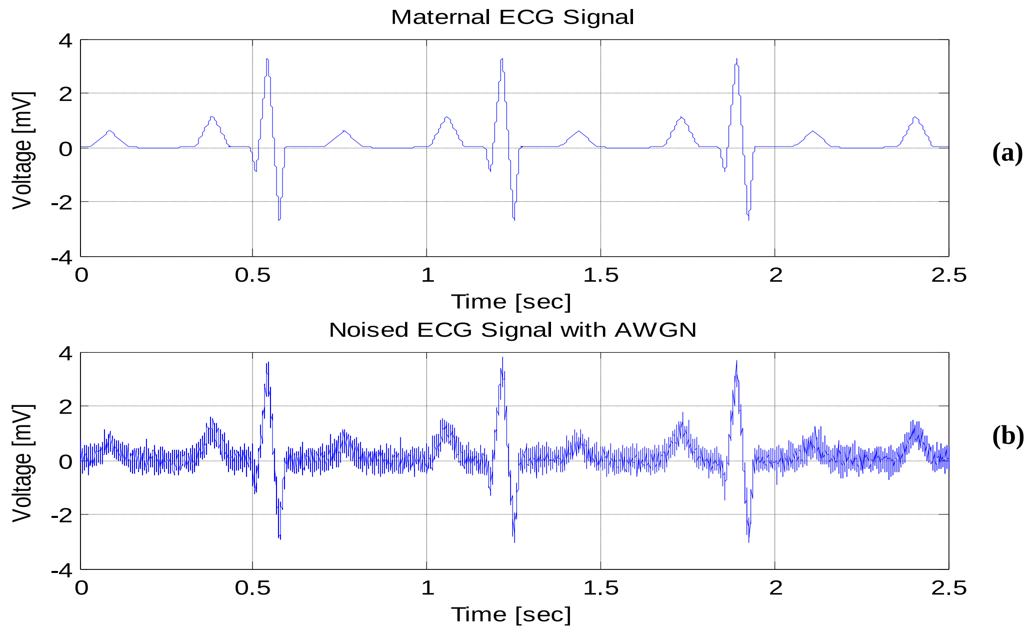


Figure 7.6 (a) and (b) indicates Original Maternal ECG signal and noised Maternal ECG signal by Additive White Gaussian Noise with SNR=10 dB.

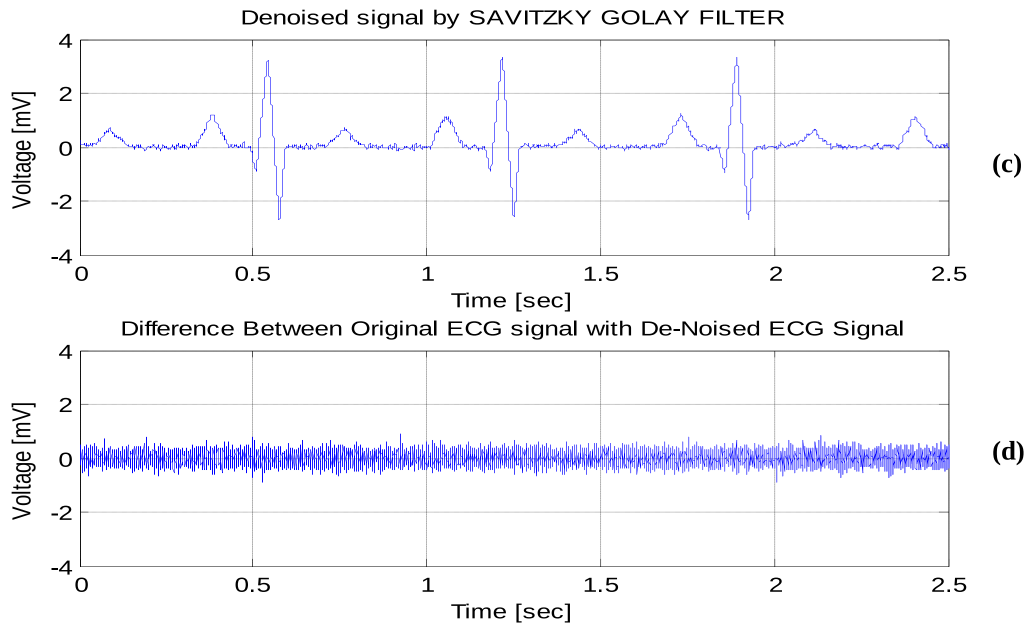
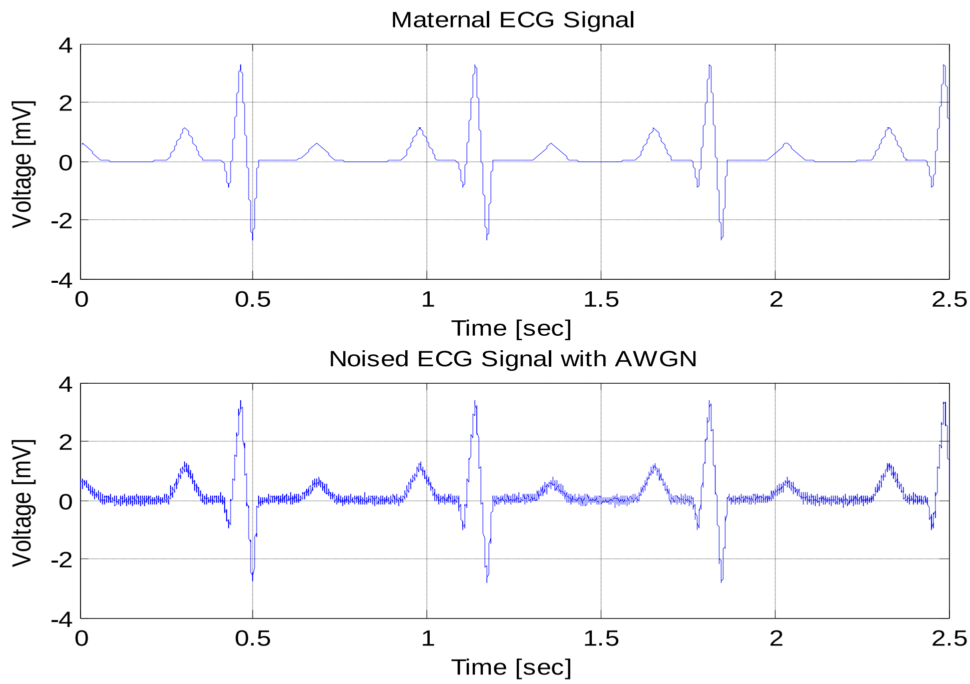


Figure 7.6: Maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=10 dB as a cubic filter to information frames of length 41(k=3, f=41))

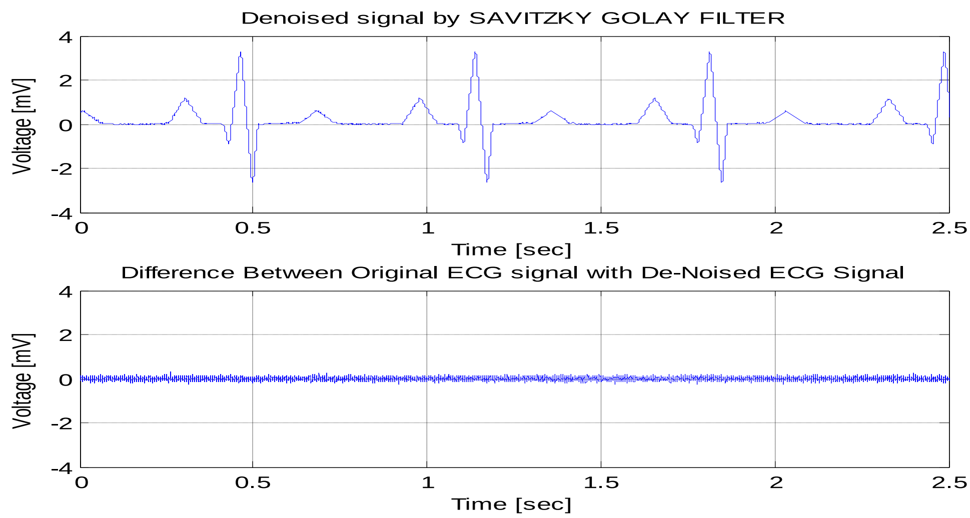
Figure 7.6 (c) and (d) shows Denoised Maternal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Maternal ECG signal with de-noised ECG signal.



(a)

(b)

Figure 7.7 (a) and (b) indicates Original Maternal ECG signal and noised Maternal ECG signal by Additive White Gaussian Noise with SNR=20 dB.



(c)

(d)

Figure 7.7: Maternal electrocardiogram ECG signal (Savitzky &Golay Filter SNR=20 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.7 (c) and (d) shows Denoised Maternal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Maternal ECG signal with de-noised ECG signal.

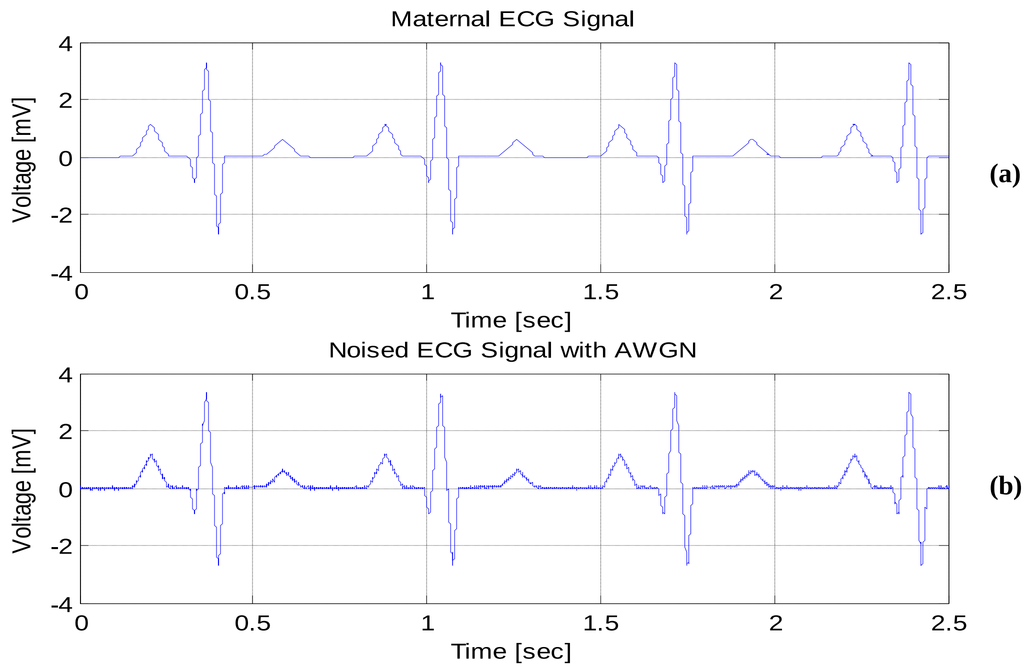


Figure 7.8 (a) and (b) indicates Original Maternal ECG signal and noised Maternal ECG signal by Additive White Gaussian Noise with SNR=30 dB.

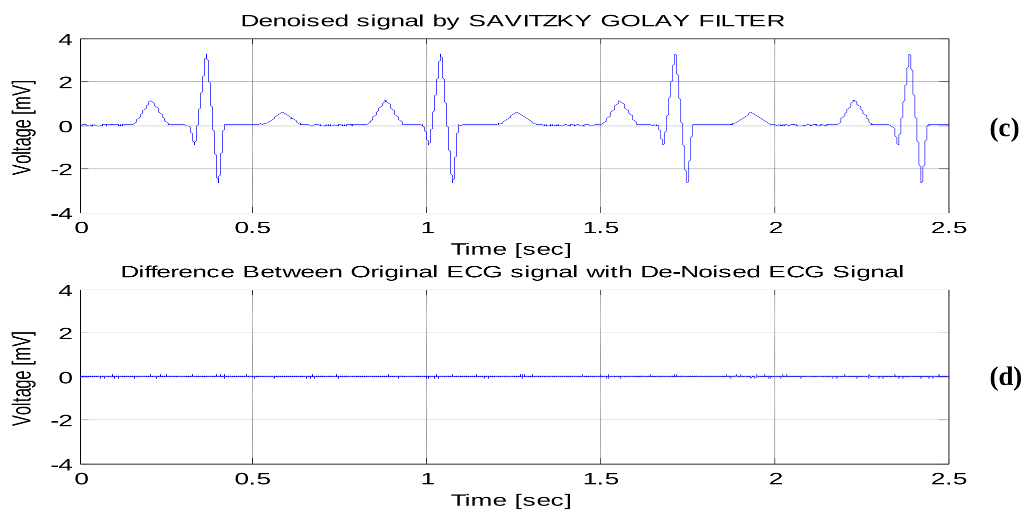


Figure 7.8: Maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=30 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.8 (c) and (d) shows Denoised Maternal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Maternal ECG signal with de-noised ECG signal.

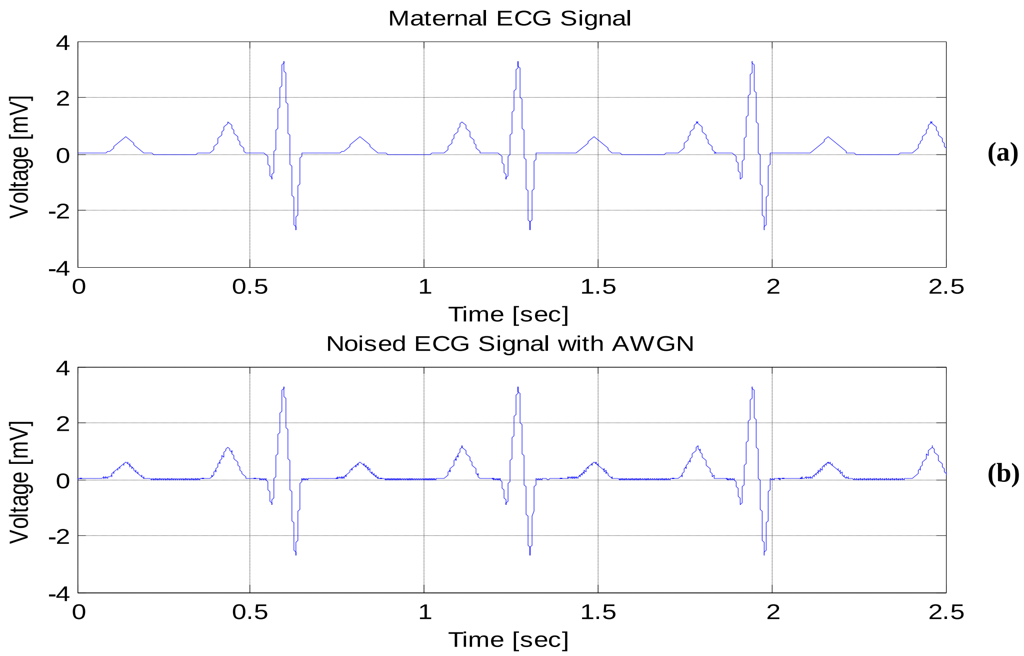


Figure 7.9 (a) and (b) indicates Original Maternal ECG signal and noised Maternal ECG signal by Additive White Gaussian Noise with SNR=40 dB.

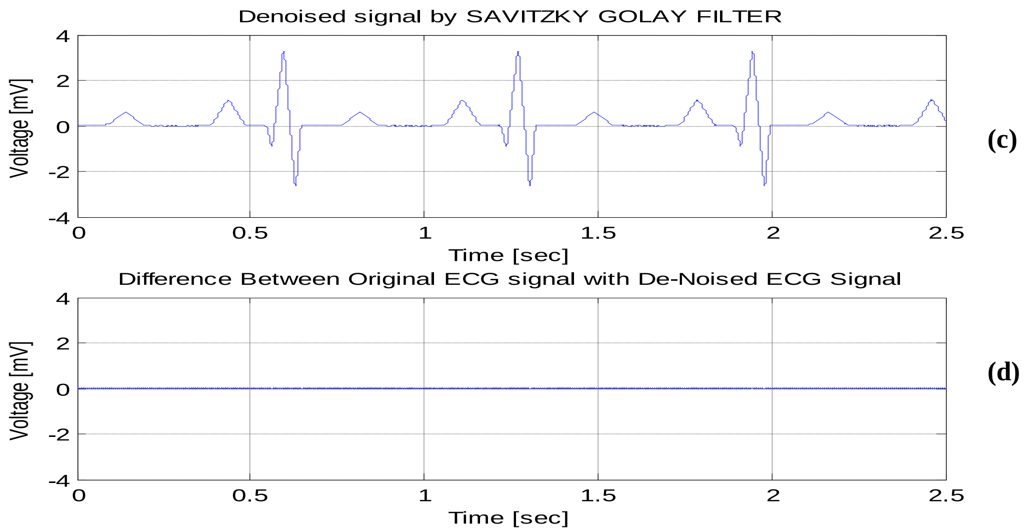
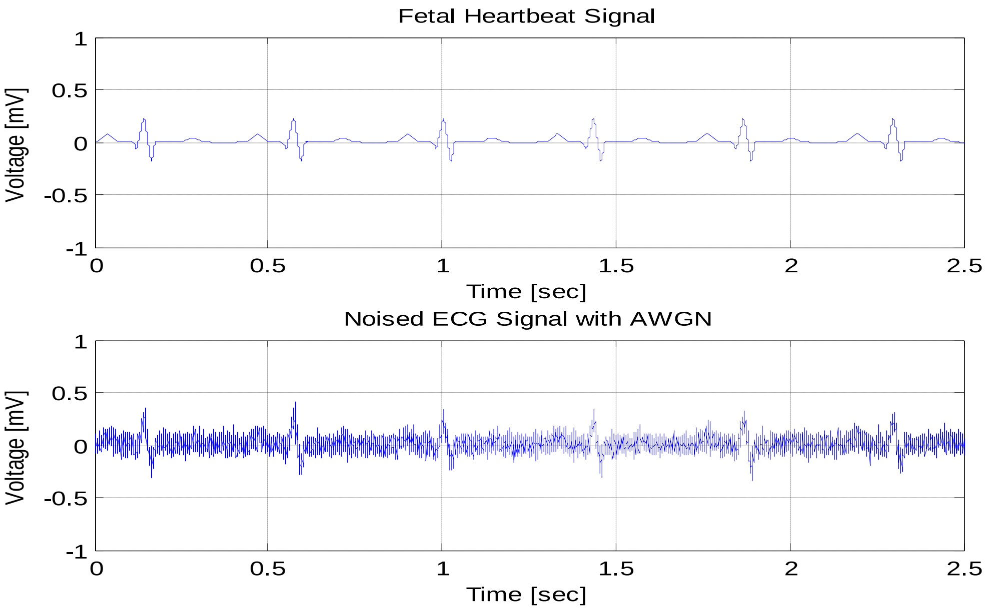


Figure 7.9: Maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=40 dB as a cubic filter to information frames of length 41(k=3, f=41))

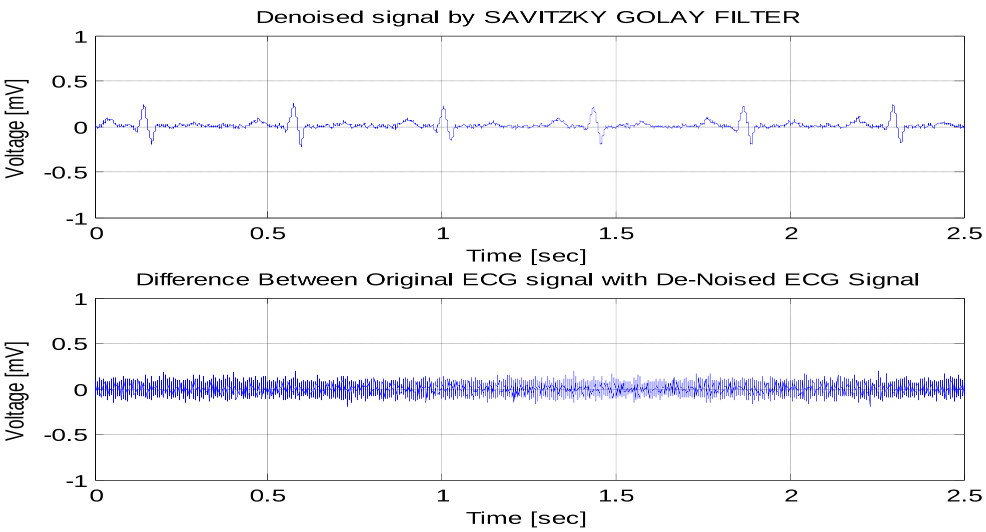
Figure 7.9 (c) and (d) shows Denoised Maternal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Maternal ECG signal with de-noised ECG signal.



(a)

(b)

Figure 7.10 (a) and (b) indicates Original Fetal ECG signal and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=0 dB.



(c)

(d)

Figure 7.10: Fetal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=0 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.10 (c) and (d) shows Denoised Fetal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Fetal ECG signal with de-noised ECG signal.

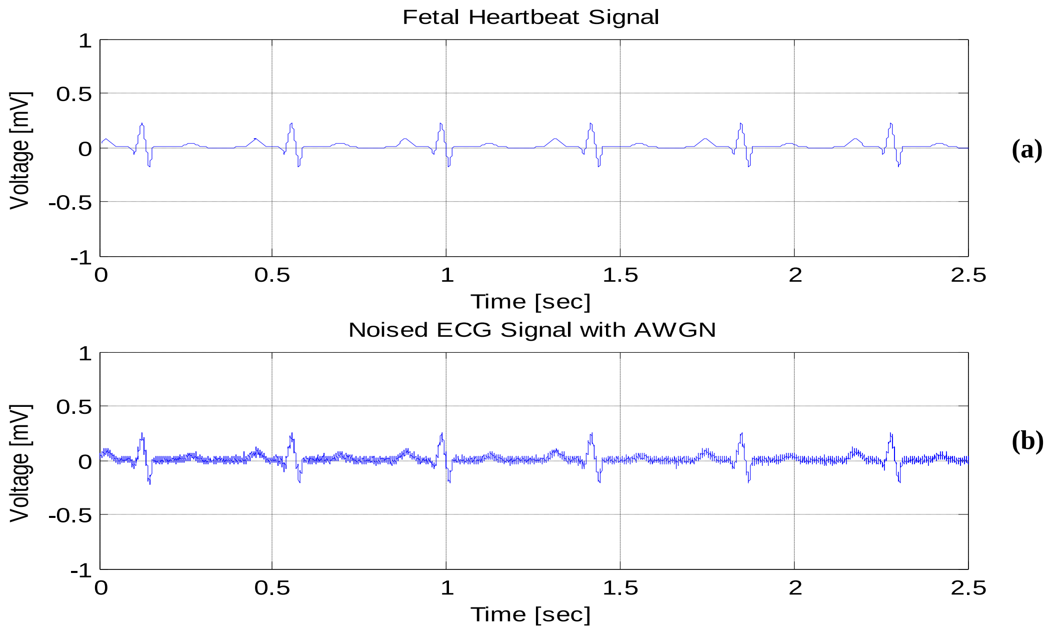


Figure 7.11 (a) and (b) indicates Original Fetal ECG signal and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=10 dB.

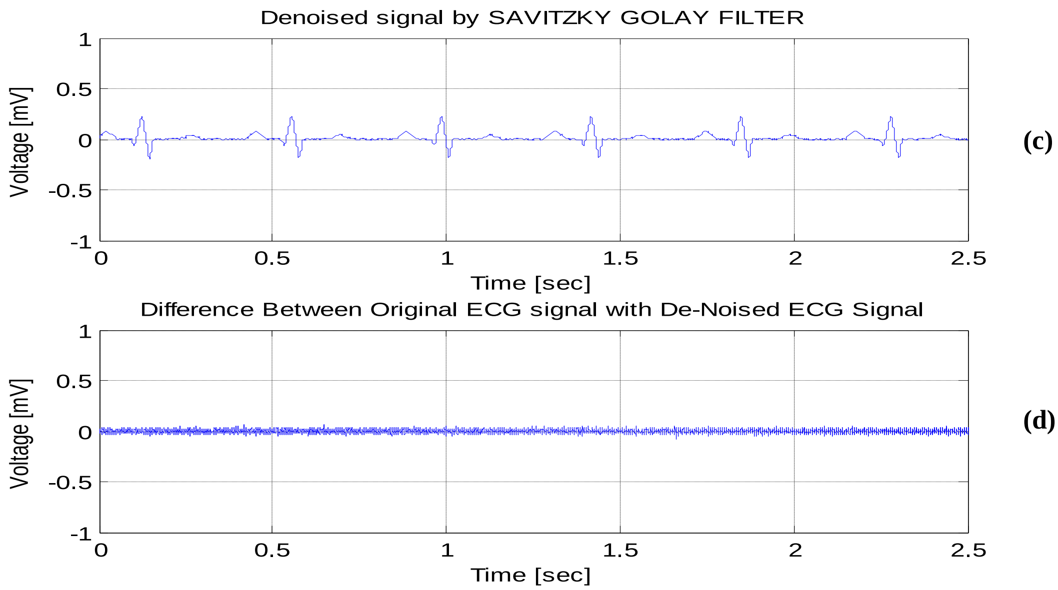


Figure 7.11: Fetal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=10 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.11 (c) and (d) shows Denoised Fetal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Fetal ECG signal with de-noised ECG signal.

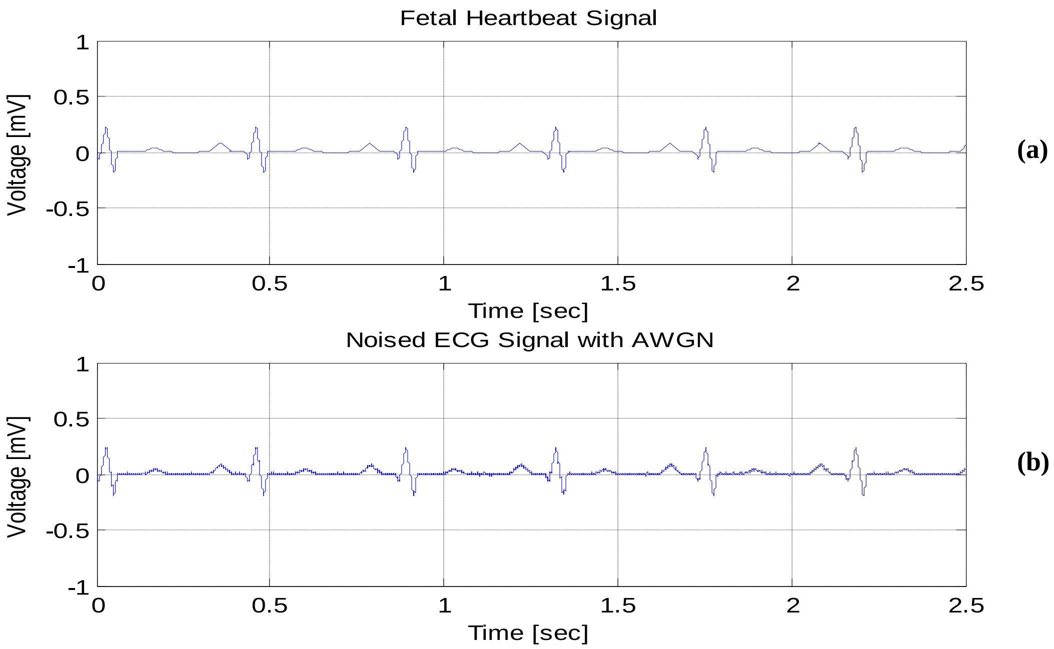


Figure 7.12(a) and (b) indicates Original Fetal ECG signal and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=20 dB.

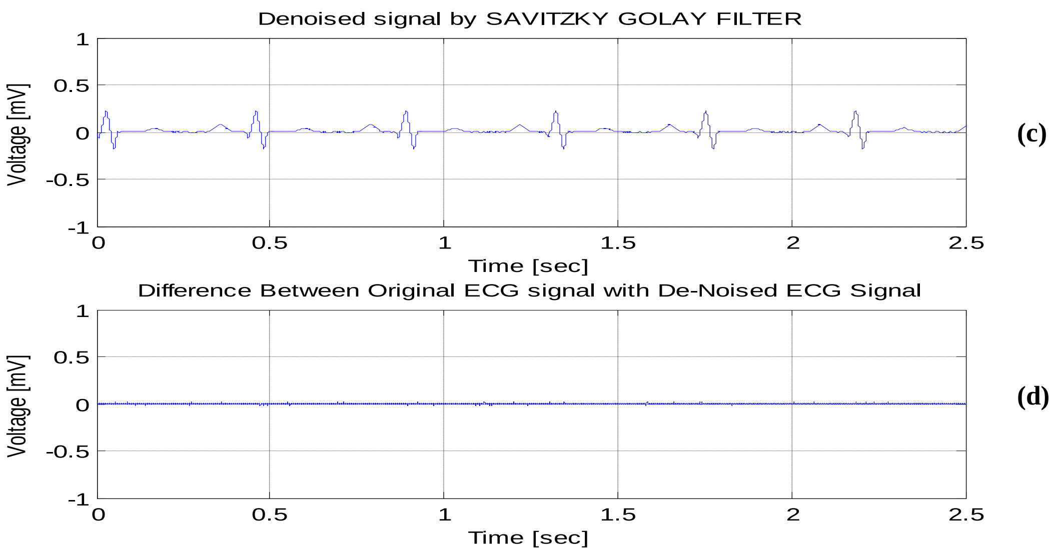


Figure 7.12: Fetal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=20 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.12(c) and (d) shows Denoised Fetal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Fetal ECG signal with de-noised ECG signal.

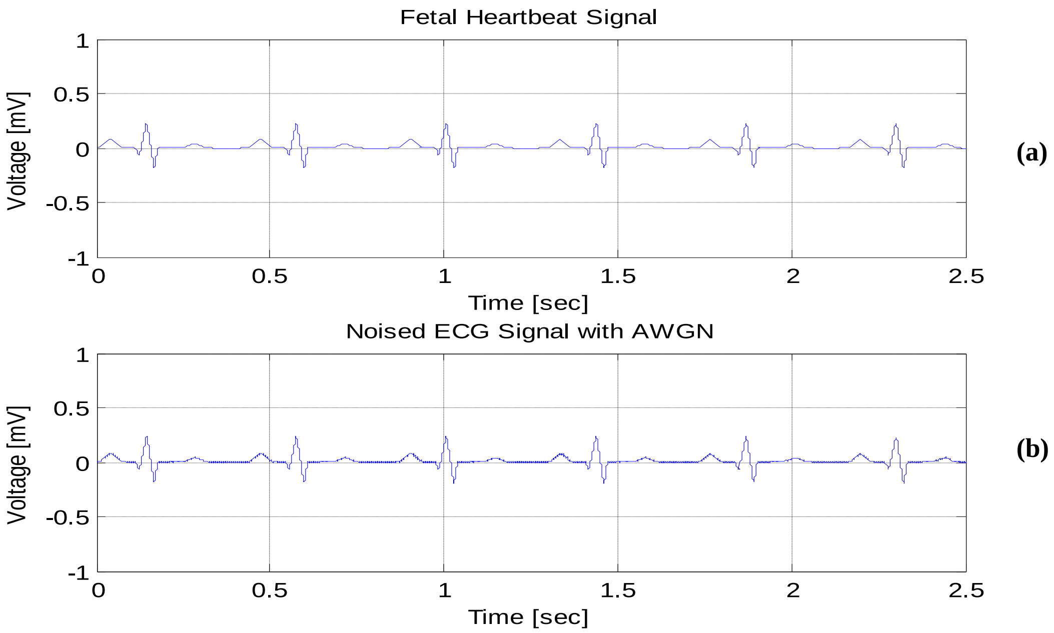


Figure 7.13(a) and (b) indicates Original Fetal ECG signal and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=30 dB.

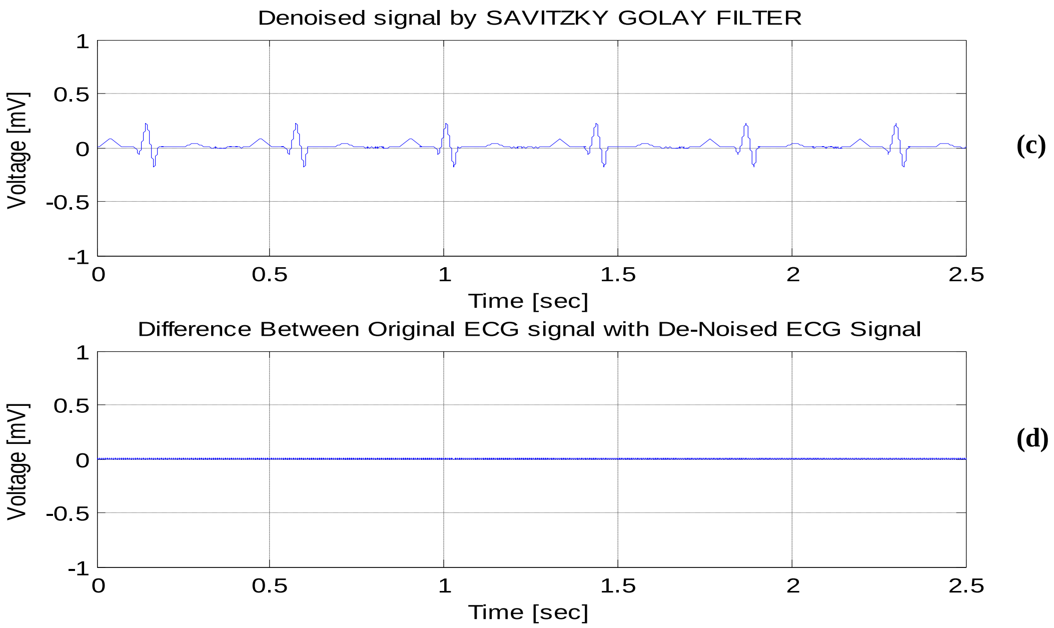


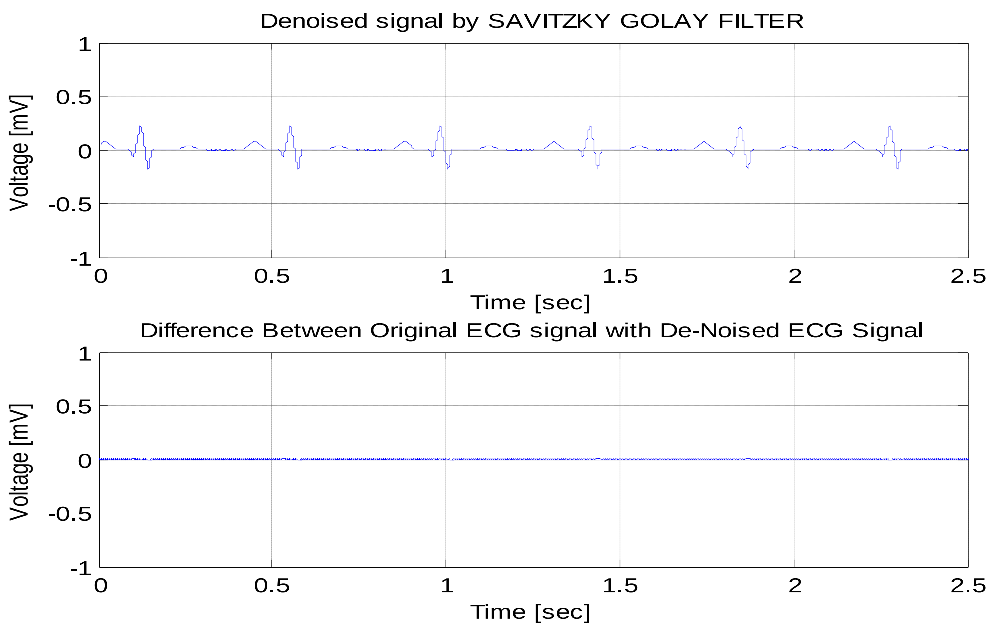
Figure 7.13: Fetal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=30 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.13(c) and (d) shows Denoised Fetal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Fetal ECG signal with de-noised ECG signal.

(a)

(b)

Figure 7.14 (a) and (b) indicates Original Fetal ECG signal and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=40 dB.



(c)

(d)

Figure 7.14: Fetal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=40 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.14(c) and (d) shows Denoised Fetal ECG signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and difference among original Fetal ECG signal with de-noised ECG signal.

The results shown below are given as a graph. Figures shows in order:

- Top Left and Right graphs shows created original Maternal and Fetal Electrocardiogram signals.
- Second line figures indicates; left figure illustrate combined original Maternal and Fetal Electrocardiogram signals, right figure indicates noised, Maternal and Fetal ECG signals with various values of AWGN Noise.
- Third line figures shows; left figure illustrate de-noised combined original Maternal and Fetal ECG signals, right figure shows difference between Original combined ECG signal with De-Noised MHB and FHB ECG Signal.

Table 7.1: Peak signal noise ratio values of Savitzky-Golay Filter & Adaptive Noise Cancellation (LMS: Least Mean Square Algorithm)

SNR (dB)	**DE-NOISING WITH SAVITZKY-GOLAY FILTER (PSNR VALUE) Maternal ECG**	**DE-NOISING WITH SAVITZKY-GOLAY FILTER (PSNR VALUE) Fetal ECG**	**DE-NOISING WITH ADAPTIVE NOISE CANCELLATION (LMS: Least Mean Square Algorithm) (PSNR VALUE) Maternal - Fetal ECG**
WHEN snrindB=0	PSNR = +54.8212 dB	PSNR = +77.8253 dB	PSNR = +53.8642 dB
WHEN snrindB=10	PSNR = +64.7911 dB	PSNR = +87.8127 dB	PSNR = +62.7522 dB
WHEN snrindB=20	PSNR = +74.8212 dB	PSNR = +97.8255 dB	PSNR = +71.8881 dB
WHEN snrindB=30	PSNR = +84.7194 dB	PSNR = +106.9815 dB	PSNR = +83.7163 dB
WHEN snrindB=40	PSNR = +93.7594 dB	PSNR = +113.2336 dB	PSNR = +91.7543 dB

Signal Noise Ratio: is a measure utilized in science and engineering which compares the level of a needed signal to the level of background noise. It is described as the proportion of signal power to the noise power, frequently defined in decibels (dB).

Peak Signal Noise Ratio: is an engineering notation for the ratio between the maximum feasible power of a signal and the power of distorting noise which influences the stability of its representation. Because many signals have a very broad dynamic range, Peak Signal Noise Ratio is usually described in terms of the logarithmic decibel measure.

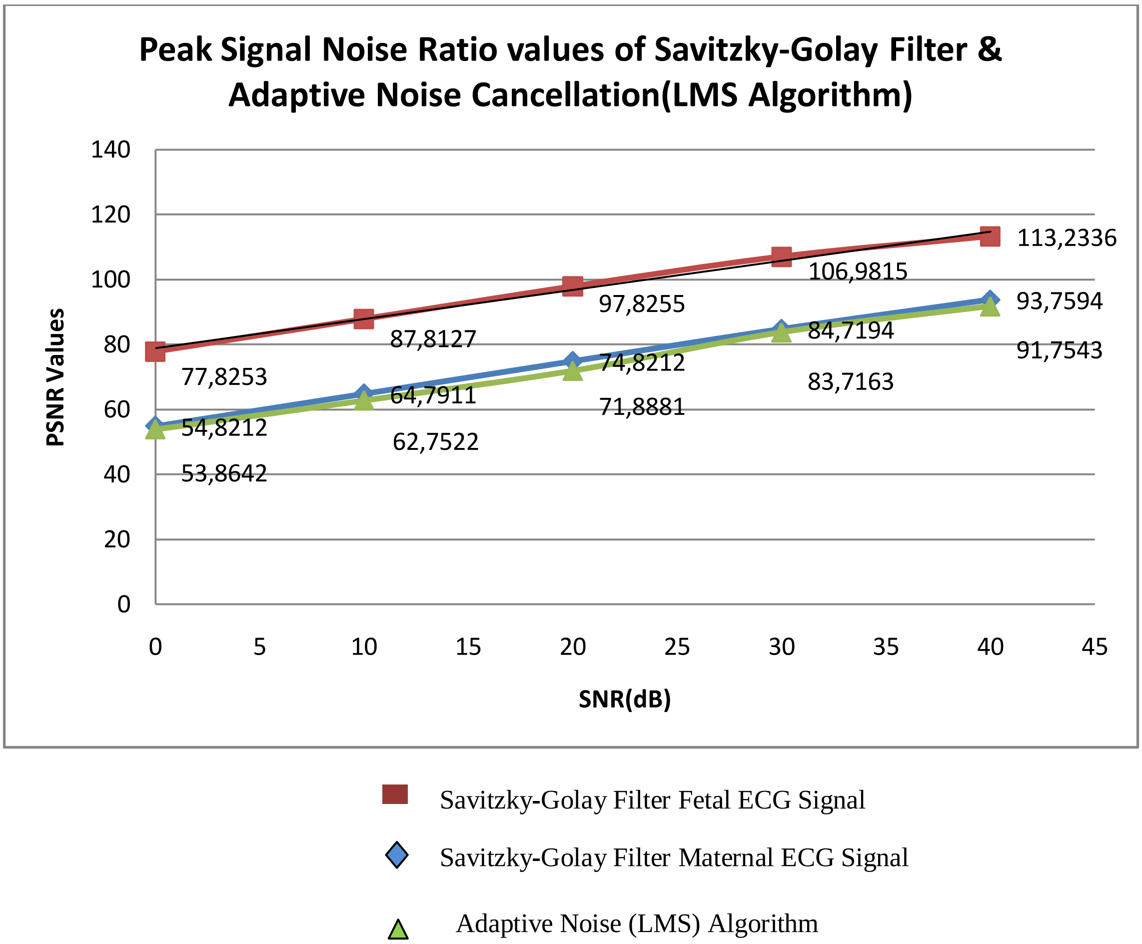
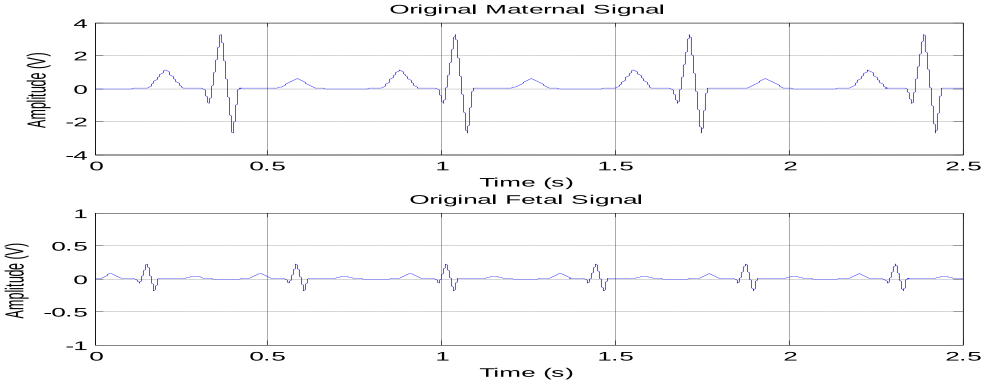


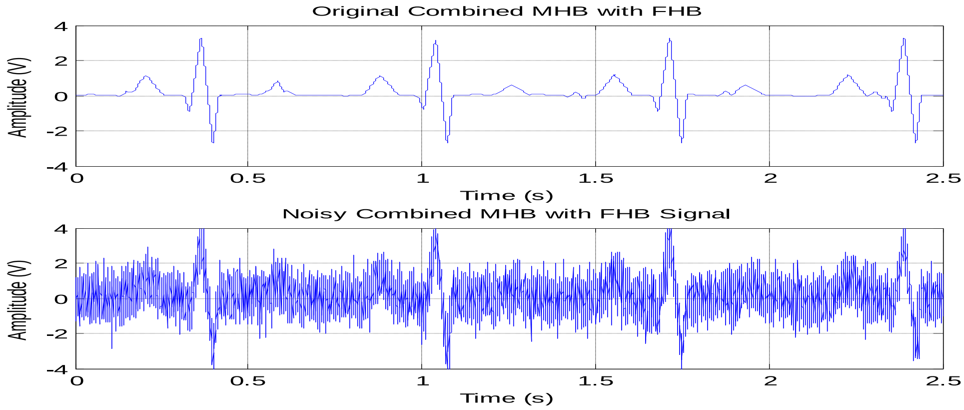
Figure 7.15: Peak signal noise ratio values of Savitzky-Golay Filter & Adaptive Noise cancellation (LMS Algorithm)



(a)

(b)

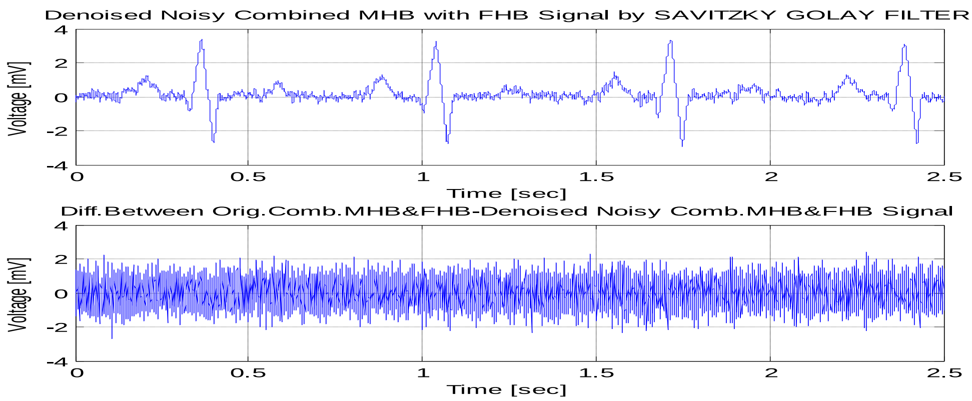
Figure 7.16 (a) and (b) indicate Original Maternal and Fetal ECG signals.



(c)

(d)

Figure 7.16 (c) and (d) shows respectively original combined MHB and FHB signals and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=0 dB.

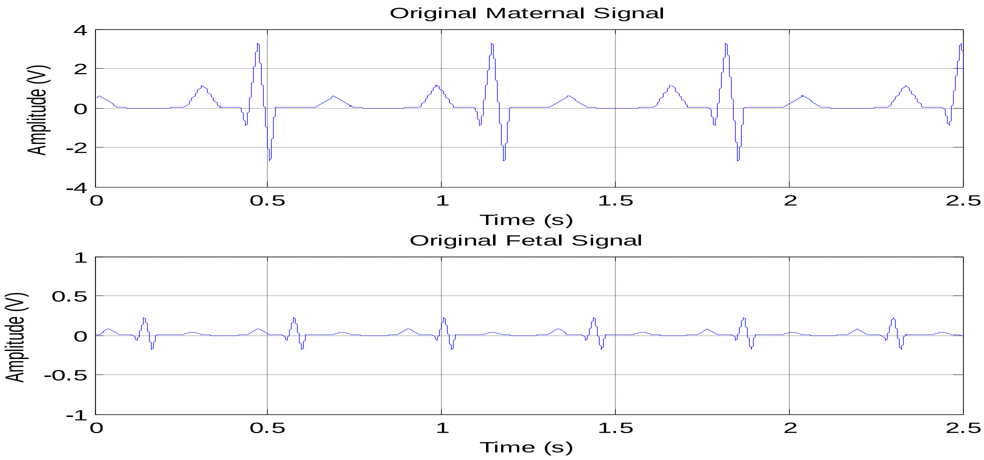


(e)

(f)

Figure 7.16: Combined fetal - maternal electrocardiogram ECG signal (Savitzky-Golay Filter SNR=0 dB as a cubic filter to information frames of length 41(k=3, f=41))

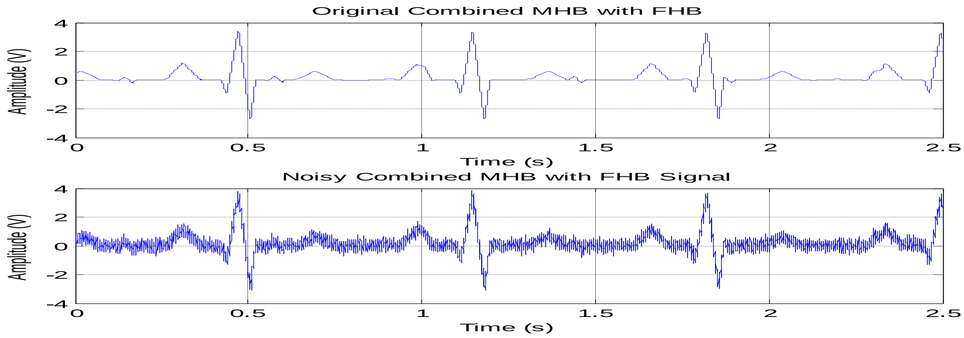
Figure 7.16 (e) and (f) illustrate respectively denoised noisy combined MHB&FHB signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and Difference among Original combined MHB&FHB signal and denoised combined MHB&FHB signal.



(a)

(b)

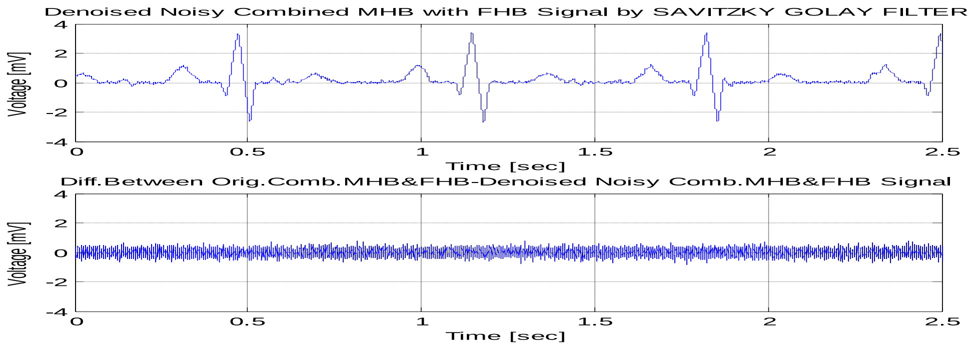
Figure 7.17 (a) and (b) indicate Original Maternal and Fetal ECG signals.



(c)

(d)

Figure 7.17 (c) and (d) shows respectively original combined MHB and FHB signals and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=10 dB.

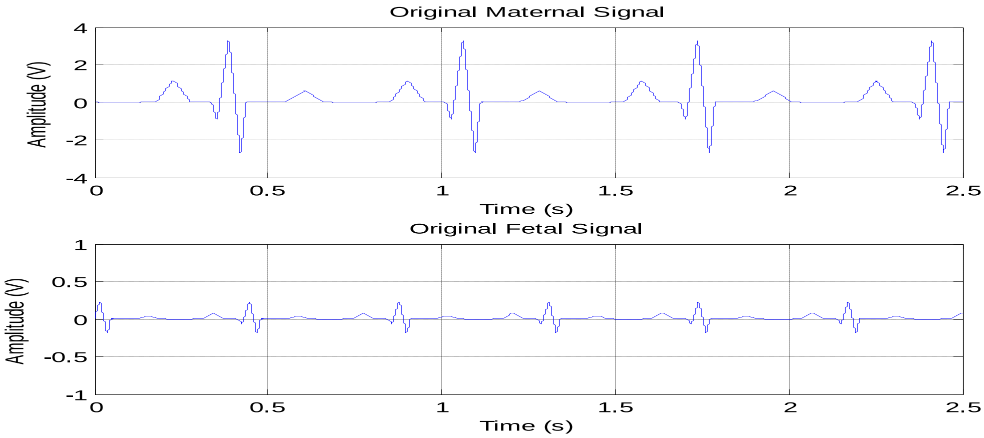


(e)

(f)

Figure 7.17: Combined fetal - maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=10 dB as a cubic filter to information frames of length 41(k=3, f=41))

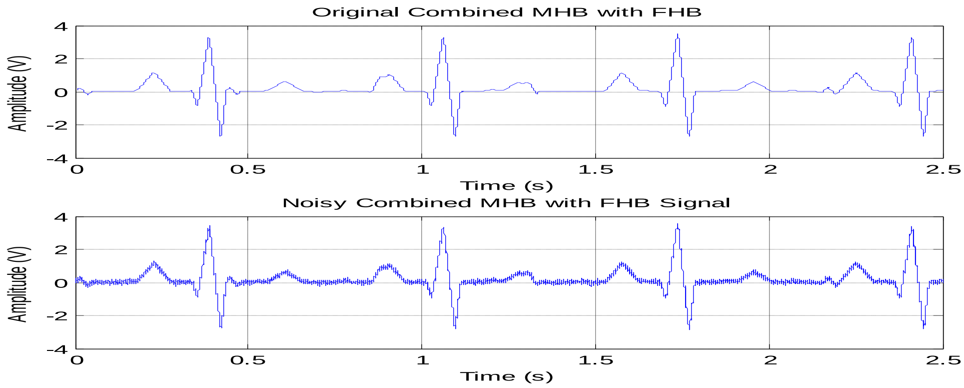
Figure 7.17 (e) and (f) illustrate respectively denoised noisy combined MHB&FHB signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and Difference among Original combined MHB&FHB signal and denoised combined MHB&FHB signal.



(a)

(b)

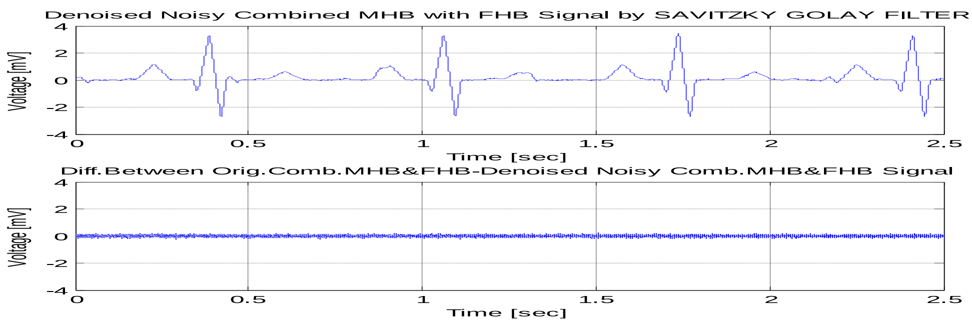
Figure 7.18 (a) and (b) indicate Original Maternal and Fetal ECG signals.



(c)

(d)

Figure 7.18 (c) and (d) shows respectively original combined MHB and FHB signals and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=20 dB.

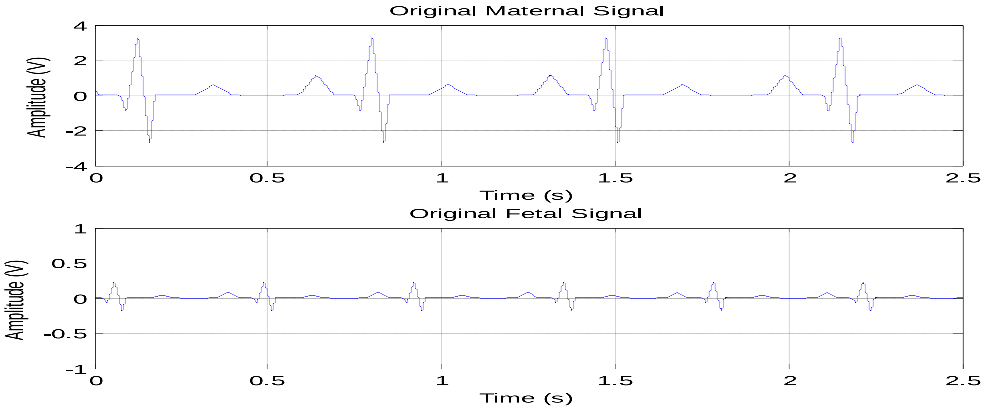


(e)

(f)

Figure 7.18: Combined fetal - maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=20 dB as a cubic filter to information frames of length 41(k=3, f=41))

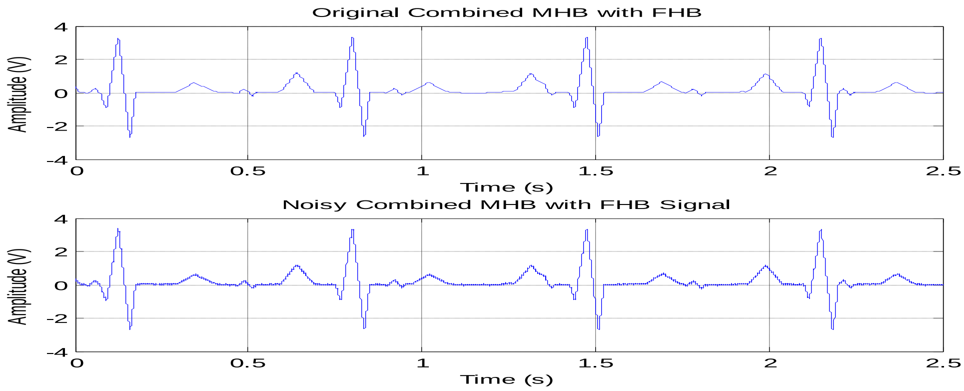
Figure 7.18 (e) and (f) illustrate respectively denoised noisy combined MHB&FHB signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and Difference among Original combined MHB&FHB signal and denoised combined MHB&FHB signal.



(a)

(b)

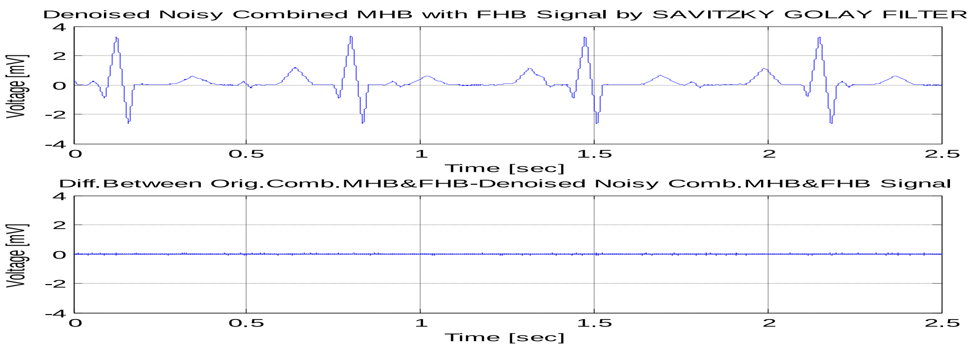
Figure 7.19 (a) and (b) indicate Original Maternal and Fetal ECG signals.



(c)

(d)

Figure 7.19 (c) and (d) shows respectively original combined MHB and FHB signals and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=30 dB.

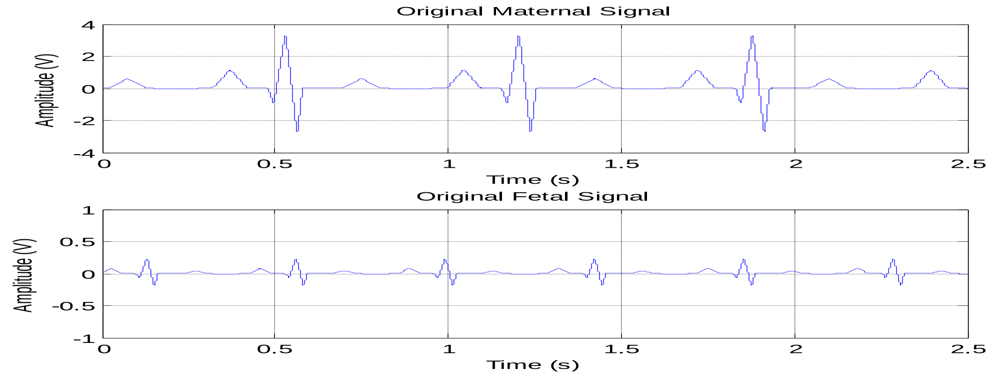


(e)

(f)

Figure 7.19: Combined fetal - maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=30 dB as a cubic filter to information frames of length 41(k=3, f=41))

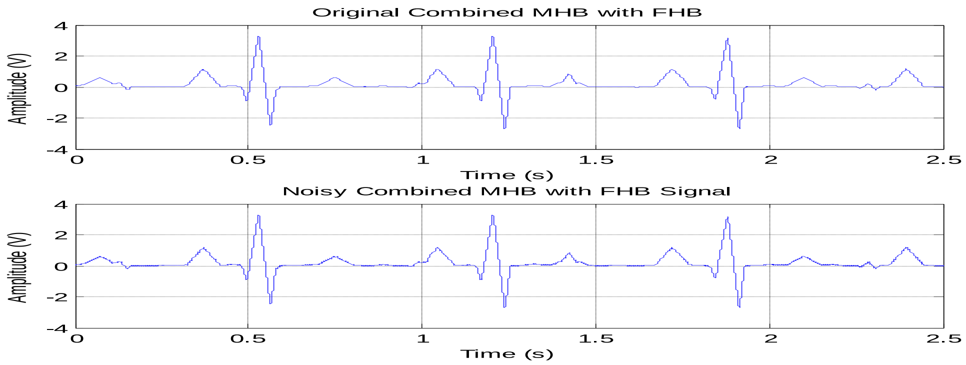
Figure 7.19 (e) and (f) illustrate respectively denoised noisy combined MHB&FHB signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and Difference among Original combined MHB&FHB signal and denoised combined MHB&FHB signal.



(a)

(b)

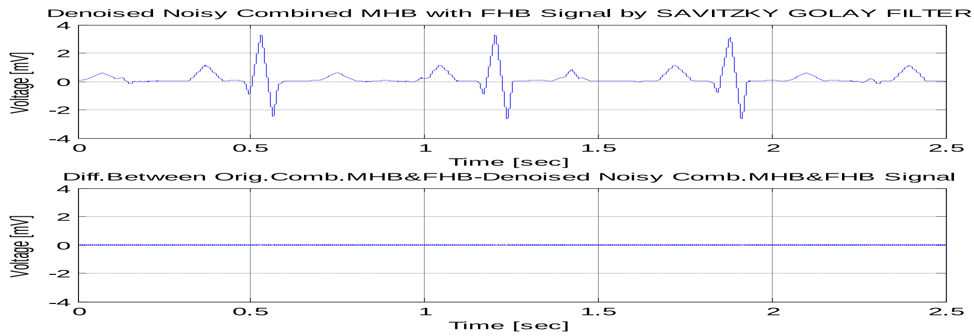
Figure 7.20 (a) and (b) indicate Original Maternal and Fetal ECG signals.



(c)

(d)

Figure 7.20 (c) and (d) shows respectively original combined MHB and FHB signals and noised Fetal ECG signal by Additive White Gaussian Noise with SNR=40 dB.



(e)

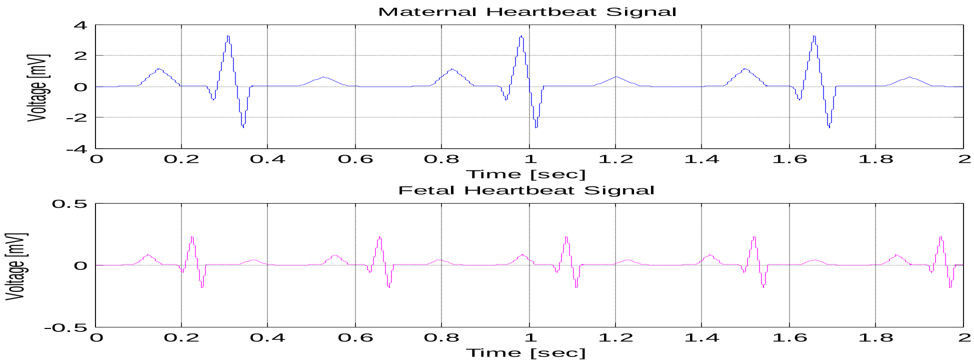
(f)

Figure 7.20: Combined fetal - maternal electrocardiogram ECG signal (Savitzky&Golay Filter SNR=40 dB as a cubic filter to information frames of length 41(k=3, f=41))

Figure 7.20 (e) and (f) illustrate respectively denoised noisy combined MHB&FHB signal by Savitzky-Golay Filter with a cubic filter to information frames of length 41(k=3, f=41)) and Difference among Original combined MHB&FHB signal and denoised combined MHB&FHB signal.

7.6 Results of Experiments (Adaptive Noise Canceller)

In this section the results obtained from Adaptive Noise Canceller will be demonstrated.



(a)

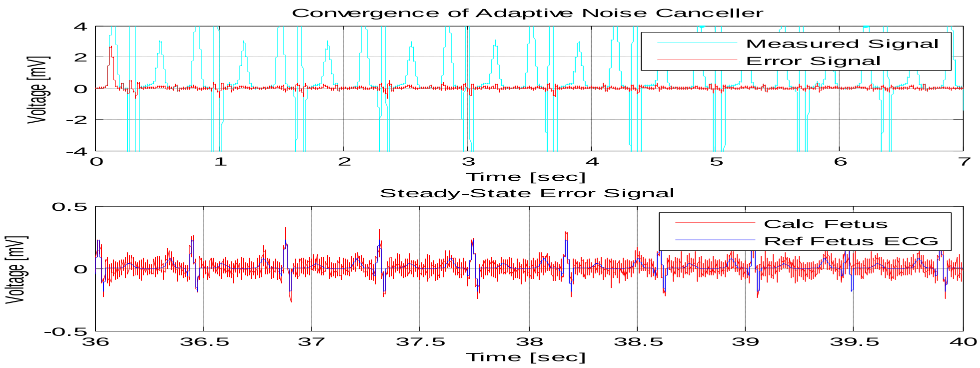
(b)

Figure 7.21 (a) and (b) indicate Original Maternal and Fetal ECG signals.

(c)

(d)

Figure 7.21 (c) and (d) shows respectively Measured signal and reference signal, measured reference signals to forecast noise available in measured primary signal.



(e)

(f)

Figure 7.21: Maternal &fetal electrocardiogram ECG signal denoised by adaptive noise canceller (Adaptive filter length is 15 and LMS step size is 0.001.)

Figure 7.21 (e) and (f) illustrate respectively convergence of Adaptive Noise Canceller and steady-state error signal for maternal and fetal ECG signals with Adaptive filter length is 15 and LMS step size is 0.001.

Table 7.2: Beat per minutes (bpm) values obtained from adaptive noise cancellation

Maternal ECG bpm values	**Fetal ECG bpm values**
Maternal Heart Rate =73bpm	Fetus Heart Rate =115 bpm
Maternal Heart Rate =63 bpm	Fetus Heart Rate =142 bpm
Maternal Heart Rate =72 bpm	Fetus Heart Rate =157 bpm

7.7 Results of Experiments (Peak Finder)

In this part how we can define heart beat from Peak Finder will be explained.

Peak Detector Board

Peak Detector board observes maxima, representing *x*-axis values at that they be created. Peaks are described as a local maximum where lower values are available on both sides of a peak. Endpoints are not noted to be peaks. This panel permits you to change settings for

- Peak threshold.
- Maximum peaks number.
- Peak deflection.

The Peak finder panel is divided into two panes, tagged Settings and Peaks. You can enlarge each pane to see present choices. The Peaks pane monitors all of the largest computed peak values. It also indicates coordinates, at that peaks take shape, utilizing coefficients you describe in Settings plate. You set Max Peaks Num parameters to describe peaks number indicated in list. Numerical quantities observed in quantity column are equal to “pks” output debate reverted when you actuate find peaks function. Numerical values characterized in second column are similar to “locs” output argument rotated when you actuate “findpeaks” function. Peak Detector monitors peak quantities in Peaks plate. Professed, Peak Detector board monitors largest computed peak values in Peaks board in reducing peak height layout.

Maternal ECG Time Scope

It can be seen that from peak values list, there is a stationary of 0.675 sec time difference among each heartbeat. 10 peak amplitude values, and times at that they take shape, as indicated in next figure.

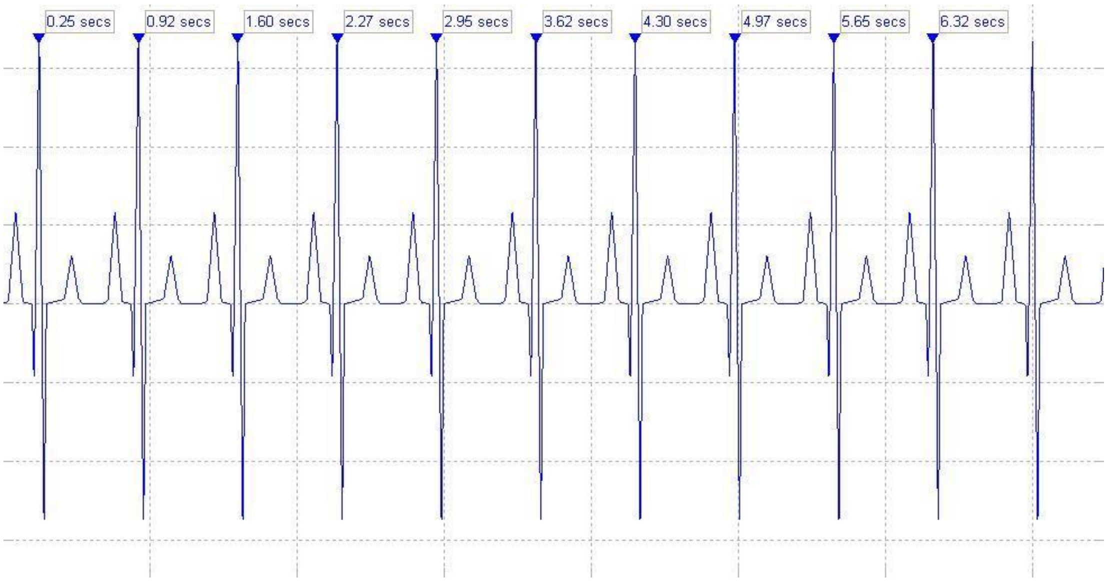


Figure 7.22: 10 peak amplitude values for maternal ECG signal

Table 7.3: Heart rate detection for maternal ECG signal (with tagged settings 3.333 s)

Heartbeats(Peaks)	Time(seconds)
1	0.250
2	0.925
3	1.600
4	2.275
5	2.950
6	3.625
7	4.300
8	4.975
9	5.650
10	6.325

For this reason, the heart rate specified by Electrocardiogram signal is composed by next equation.

$$\frac{60\ sec/min}{0.675 sec/beat} = 88.89\ beats/\min\ (bpm)$$

Fetal ECG Time Scope

It can be seen that from peak values list, there is a stationary 0.431 sec time difference among each heartbeat. 10 peak amplitude values, and times at that they take shape, as indicated in next figure.

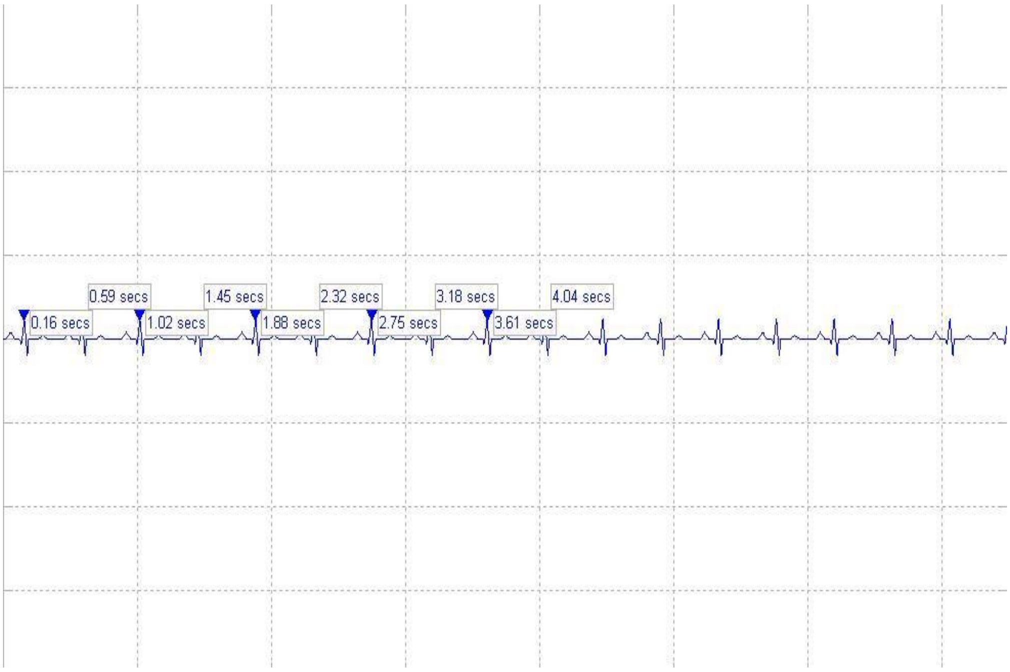


Figure 7.23: 10 peak amplitude values for fetal ECG signal

Table 7.4: Heart rate detection for fetal ECG signal (with tagged settings 231,283ms)

Heartbeats(Peaks)	Time(seconds)
1	0.160
2	0.591
3	1.022
4	1.453
5	1.885
6	2.316
7	2.747
8	3.178
9	3.610
10	4.041

For this reason, the heart rate specified by the Electrocardiogram signal is stated by next equation.

$$\frac{60\ sec/min}{0.431 sec/beat} = 139.21\ beats/\mathrm{min}\ (bpm)$$

7.8 Summary

In this section, Savitzky-Golay filtering and Adaptive Noise Canceller (LMS) techniques of denoising are offered and applied to real Maternal and Fetal (ECG) signals at different noise levels. Results obtained from Savitzky-Golay Filtering and Adaptive Noise Canceller (LMS) would be demonstrated.

Comparison indicates that Savitzky-Golay filtering performs preferable denoising than Adaptive Noise Canceller (LMS).

CHAPTER 8
CONCLUSION AND SUGGESTIONS

8.1 Conclusion

Heart diseases are rising in the world nowadays and it is being the primary reason of death and the Electrocardiogram is main significant instrument to diagnose the heart issues and its price is additionally low and readily existent. However Electrocardiogram signal is corrupted by many kinds of noises that influences the diagnosis and yields improper data. Numerous kinds of filter were improved to clear the noise available in Electrocardiogram and smoothing.

Electrocardiogram (ECG) is a major instrument to measure health and disease perception. Because of a lot of noise sources, ECG has been cleared from noise in the signal and offered in the form of an intelligible wave. Power line interference, exterior electromagnetic fields, haphazard body motions or breathing may be included in Noise resources. Savitzky-Golay extracts noise and smooths the signal without much loss of data and signal properties and individuality. Frame size and polynomial degree are Savitzky-Golay filter coefficients and all achievement is addicted on these coefficients.

Savitzky-Golay aliasing (smoothing) filters are characteristically utilized to "smooth out" a noisy signal whose frequency span (without noise) is wide. In this kind of implementation, Savitzky-Golay aliasing (smoothing) filters implement much preferable than canonical mean Finite Impulse Response filters that view to filtering an important section high signal frequency content throughout with noise. Even though Savitzky-Golay filters are more efficient at protecting concerned high frequency constituents of the signal.

Adaptive noise cancelling, an alternate technique of guessing signals distorted according to additive noise or attempt. The process utilizes "prime" input having damaged signal and a "representative" input with some correlations including noise obscure method with prime noise.

Representative input in order to get signal forecast is adaptively filtered and removed from fundamental input. Adaptive filteration prior to authorize the treatment therapy of entries which are stochastic or deterministic, time-invariant or constant.

In this Thesis, two extensive and significant denoising techniques are offered and applied on actual Electrocardiogram signals corrupted with distinct amount of noise. Adaptive Noise Canceller (LMS) and Savitzky-Golay filtering are these algorithms. MATLAB Software is utilized in order to implementation, comparison and analysis of their noise removal performances.

In this study, Adaptive Noise Canceller (LMS) and Savitzky-Golay filtering techniques of noise removal are offered and applied to real Maternal and Fetal (ECG) signals at different noise levels. The comparison indicates which the Savitzky-Golay filtering performs preferable noise removal than Adaptive Noise Canceller (LMS).

Our suggested study including the Savitzky-Golay Filter and Adaptive Noise Canceller have verified its achievment in denosing the Maternal and Fetal Electrocardiogram Signal with simulated information sets. In this Thesis the various kinds of errors in Maternal and Fetal Electrocardiogram Signal and a solution that can be applied in Electrocardiograph tools were analyzed with white Gaussian noise and outcomes which dedicated above were acquired. In the whole system, the primary goal will be getting clear, preferable standard output signals for well discussions.

8.2 Suggestions

Future work will contain common and important noise reduction method discrete wavelet transform (universal and local thresholding), its noise reduction performance will be implemented, compared and analyzed for research of Continuous Glucose Monitoring(CGM) systems. These systems is plenty requisite for avoiding of Diabetic complications and can be very beneficial in diabetes management. For develop system class, discrete wavelet transform will be used for this purpose for improving influence of system.

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APPENDIX 1

MATLAB CODES FOR FILTERING ECG SIGNAL

```
% Creating ECG Signal
% x1 = 3.5*ecg(2700).';
% y2 = sgolayfilt(kron(ones(1,13),x1),0,21);
% n = 1:30000;
% del = round(2700*rand(1));
% mhb = y2(n + del);
% t = 0.00025:0.00025:7.5;
% subplot(2,1,1)
% plot(t,mhb)
% axis([0 2.5 -4 4]);
% grid;
% xlabel('Time [sec]');
% ylabel('Voltage [mV]');
% title('Maternal ECG Signal');


x2 = 0.25*ecg(1725);
y2 = sgolayfilt(kron(ones(1,20),x2),0,17);
n = 1:30000;
del = round(1725*rand(1));
fhb = y2(n + del);
t = 0.00025:0.00025:7.5;
subplot(2,1,1)
plot(t,fhb);
axis([0 2.5 -1 1]);
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Fetal Heartbeat Signal');

% %Adding AWGN Noise
t = 0.00025:0.00025:7.5;
y = awgn(fhb,40,'measured'); % Add white Gaussian noise.
subplot(2,1,2)
plot(t,y) % Plot both signals.
axis([0 2.5 -1 1]);
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Noised ECG Signal with AWGN');

figure
```

```
% % De-Noising with Savitzky-Golay Filter
k=3;
f=41;
z=sgolayfilt(y,k,f);
subplot(2,1,1)
plot(t,z)
axis([0 2.5 -1 1]);
grid
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Denoised signal by SAVITZKY GOLAY FILTER');


% % Difference Between Original ECG signal  with De-Noised ECG Signal
error = y - z;
error = double(y) - double(z);
subplot(2,1,2)
plot(t,error)
axis([0 2.5 -1 1]);
grid
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Difference Between Original ECG signal with De-Noised ECG Signal');
decibels = 20*(log10(255./(sqrt((1/256^2)*(sum(sum(error.^2)))))));
disp(sprintf('PSNR = +%5.4f dB',decibels))


% x = 3.5*ecg(2700);
% x2 = 0.25*ecg(1725);
% y = repmat(sgolayfilt(x2,0,17),[1 20]);
% sigData = y(1:30000)';
%
% TS_ECG = dsp.TimeScope('SampleRate', 4000, ...
%     'TimeSpanSource', 'Auto', 'ShowGrid', true);
% step(TS_ECG, sigData);
% TS_ECG.YLimits = [-4, 4];
% release(TS_ECG);
%
%
% mhb=[0.250,0.925,1.600,2.275,2.950,3.625,4.300,4.975,5.650,6.325];
% fhb=[0.160,0.591,1.022,1.453,1.885,2.316,2.747,3.178,3.610,4.041];
%
% MaternalHeartRate=60/[mhb(2)-mhb(1)]
% FetalHeartRate=60/[fhb(2)-fhb(1)]
```

APPENDIX 2

MATLAB CODES FOR FILTERING COMBINED ECG SIGNAL

```
%Create Initial Signals

x1 = 3.5*ecg(2700).';
y2 = sgolayfilt(kron(ones(1,13),x1),0,21);
k = 1:30000;
del1 = round(2700*rand(1));
mhb = y2(k + del1);
t = 0.00025:0.00025:7.5
subplot(2,1,1),plot(t,mhb)
xlabel('Time (s)')
ylabel('Amplitude (V)')
title('Original Maternal Signal')
axis([0 2.5 -4 4]);
grid

x2 = 0.25*ecg(1725);
y3 = sgolayfilt(kron(ones(1,20),x2),0,17);
n = 1:30000;
del2 = round(1725*rand(1));
fhb = y3(n + del2);
t = 0.00025:0.00025:7.5;
subplot(2,1,2),plot(t,fhb)
xlabel('Time (s)')
ylabel('Amplitude (V)')
title('Original Fetal Signal')
axis([0 2.5 -1 1]);
grid

figure

combined=mhb+fhb
subplot(2,1,1)
plot(t,combined)
xlabel('Time (s)')
ylabel('Amplitude (V)')
title('Original Combined MHB with FHB')
axis([0 2.5 -4 4]);
grid


% % %Create Initial Signals
N1 = awgn(mhb,40,'measured'); % Add white Gaussian noise.
N2 = awgn(fhb,40,'measured'); % Add white Gaussian noise.
```

```
% %Combined Maternal+Fetal ECG Signals
noisy=N1+N2
subplot(2,1,2)
plot(t,noisy)
xlabel('Time (s)')
ylabel('Amplitude (V)')
title('Noisy Combined MHB with FHB Signal')
axis([0 2.5 -4 4]);
grid

figure

k=3;
f=41;
z=sgolayfilt(noisy,k,f);
subplot(2,1,1)
plot(t,z)
axis([0 2.5 -4 4]);
grid
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Denoised Noisy Combined MHB with FHB Signal by SAVITZKY GOLAY
FILTER');

% Difference Between Original ECG signal  with De-Noised ECG Signal
error = noisy - z;
error = double(noisy) - double(z);
subplot(2,1,2)
plot(t,error)
axis([0 2.5 -4 4]);
grid
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Diff.Between Orig.Comb.MHB&FHB-Denoised Noisy Comb.MHB&FHB Signal');
decibels = 20*(log10(255./(sqrt((1/256^2)*(sum(sum(error.^2)))))));
disp(sprintf('PSNR = +%5.4f dB',decibels))
```

APPENDIX 3

MATLAB CODES FOR ECG SIGNAL ADAPTIVE NOISE CANCELLER

```
Fs = 4000;
Time = 40;
NumSamp = Time * Fs;
Hd = dfilt.dffir(fhb);

x1 = 3.5*ecg(2700).';
y1 = sgolayfilt(kron(ones(1,ceil(NumSamp/2700)+1),x1),0,21);
n = 1:Time*Fs';
del = round(2700*rand(1));
mhb = y1(n + del)';
t = 1/Fs:1/Fs:Time';
subplot(2,1,1); plot(t,mhb);
axis([0 2 -4 4]);
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Maternal Heartbeat Signal');

x2 = 0.25*ecg(1725);
y2 = sgolayfilt(kron(ones(1,ceil(NumSamp/1725)+1),x2),0,17);
del = round(1725*rand(1));
fhb = y2(n + del)';
subplot(2,1,2); plot(t,fhb,'m');
axis([0 2 -0.5 0.5]);
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Fetal Heartbeat Signal');

figure

Wopt = [0 1.0 -0.5 -0.8 1.0  -0.1 0.2 -0.3 0.6 0.1];
Wopt = rand(1,10);
d = filter(Wopt,1,mhb) + fhb + 0.02*randn(size(mhb));
subplot(2,1,1); plot(t,d,'r');
axis([0 2 -4 4]);
axis tight;
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Measured Signal');
```

```
x = mhb + 0.02*randn(size(mhb));
subplot(2,1,2); plot(t,x);
axis([0 2 -4 4]);
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Reference Signal');
%
h = adaptfilt.lms(15, 0.001);
[y,e] = filter(h,x,d);
%
% [y,e] = FECG_detector(x,d);

figure

subplot(2,1,1); plot(t,d,'c',t,e,'r');
axis([0 7.0 -4 4]);
grid;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Convergence of Adaptive Noise Canceller');
legend('Measured Signal','Error Signal');
%
subplot(2,1,2); plot(t,e,'r'); hold on; plot(t,fhb,'b');
axis([Time-4 Time -0.5 0.5]);
grid on;
xlabel('Time [sec]');
ylabel('Voltage [mV]');
title('Steady-State Error Signal');
legend('Calc Fetus','Ref Fetus ECG');

% filt_e = filter(Hd,e);
% thresh = 4*mean(abs(filt_e))*ones(size(filt_e));
% peak_e = (filt_e >= thresh);
% edge_e = (diff([0; peak_e]) >0);
% fetus_calc = round((60/length(edge_e(16001:end))*Fs)* sum(edge_e(16001:end)));
% fetus_bpm = ['Fetus Heart Rate =' mat2str(fetus_calc)];
% fprintf(fetus_bpm,'%6.2f',fetus_bpm);
```