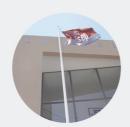
INSTITUTO SUPERIOR DE ENGENHARIA DO PORTO















ECG Denoising Based on Adaptive Signal Processing Technique

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To my wife.

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I am heartily thankful to my supervisor, Lino Figueiredo, who patiently provided me guidance and support from the initial to the final level of my work.

I would also like to offer my regards to my wife for the support provided during the completion of this work.

Abstract

An Electrocardiogram (ECG) monitoring system deals with several challenges related with noise sources. The main goal of this text was the study of Adaptive Signal Processing Algorithms for ECG noise reduction when applied to real signals. This document presents an adaptive filtering technique based on Least Mean Square (LMS) algorithm to remove the artefacts caused by electromyography (EMG) and power line noise into ECG signal. For this experiments it was used real noise signals, mainly to observe the difference between real noise and simulated noise sources. It was obtained very good results due to the ability of noise removing that can be reached with this technique.

A recolha de sinais electrocardiográficos (ECG) sofre de diversos problemas relacionados com ruídos. O objectivo deste trabalho foi o estudo de algoritmos adaptativos para processamento digital de sinal, para redução de ruído em sinais ECG reais. Este texto apresenta uma técnica de redução de ruído baseada no algoritmo Least Mean Square (LMS) para remoção de ruídos causados quer pela actividade muscular (EMG) quer por ruídos causados pela rede de energia eléctrica. Para as experiencias foram utilizados ruídos reais, principalmente para aferir a diferença de performance do algoritmo entre os sinais reais e os simulados. Foram conseguidos bons resultados, essencialmente devido às excelentes características que esta técnica tem para remover ruídos.

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Acronyms

AV Atrioventricular

dB decibel

DSP Digital Signal Processor

ECG Electrocardiogram

EEG Electroencephalography

EMG Electromyography

FIR Finite Impulse Response

HRECG High Resolution ECG

IIR Infinite Impulse Response

LCD Liquid Crystal Display

LMS Least Mean Square

MIT-BIH Massachusetts Institute of Technology - Beth Israel Hospital database

MSE Mean Square Error

PCG Phonocardiogram

RLS Recursive Least Square

RMS Root-Mean-Squared

SA Sinoatrial

SG Stochastic Gradient

SNR Signal-to-Noise Ratio

Introduction

Biomedical signals are produced by physiological activities in the organism. All living organisms, from gene and protein sequences to neural and cardiac rhythms are capable to produce signals. These signals could be observed or monitored to realize some aspects of a particular physiologic system. In medical assistance, the cardiac signal, ECG, is the more common signal used by doctors to evaluate heart anomalies. The ECG is a representation of heart electrical activity in time, which is highly used to detect heart disorders. According to the most recent statistics, reported by the World Health organization, cardiovascular diseases remaining the main specific cause of mortality in any region of the world[3].

Several studies demonstrate the importance of reducing the time delay to treatment for improving the clinical outcome of the patients in case of acute coronary syndromes[4]. Some of the most common cardiac problems, are myocardial infarction (heart attack), ventricular tachycardia, ventricular fibrillation or atrial fibrillation, where the early detection of the first symptoms occurrence is crucial, which significantly decreases mortality rate and admission time in a hospital or medical centres[5]. These are sufficient reasons for considering ECG signal as a relevant signal to be monitored by portable systems.

ECG signal is a low amplitude voltage signal, and due to the amount of noise sources that can destroy it, the ECG signal recording should take this problem into account. ECG noises sources are many; the most common sources noises arise from

instrumentation, interference of power lines and biological systems nearby the heart. Organic systems like heart are complex, and they are always affected by other organic systems or subsystems that surrounding him. Therefore, heart signals usually contain signals of other parts of the human body e.g Electromyography (EMG) signals. Removing unwanted signal components from ECG signal can underlie better interpretation of the signal. Hence, signal processing is present in a vast of ECG systems for noise reduction.

A fundamental method for noise cancelation analyzes the signal spectra and suppresses undesired frequency components. The problem is that noise can overlap the entire signal, and in these cases the classical methods for signal denoising are not adequate. To overtake this difficulty it should be taken into account new methods based in advanced signal processing techniques such as Adaptive Signal Processing. Adaptive signal processing methods can perform some tuning in their filtering parameters in such way that will improve their performance. These filters are defined as a self-designing system that relies on a recursive algorithm for its operation. This algorithm allows the filter to perform good accuracy for signals even when relevant signals statistics are not available.

One of the first algorithms used in adaptive signal processing was Least Mean Square (LMS) developed by Widrow and Hoff in 1959. Nowadays this algorithm is widely used due to its robustness and simplicity.

1.1 Terminology

Some terms have to be defined before going further. These terms are resumed here, but some of them are highlighted during the text.

Heart Apex is the lowest superficial part of the heart. Systole is the term used to describe the heart contraction. Diastole is the period of time when the heart fills with blood after systole. AV node is the only point of electrical contact between atria and ventricles. AV bundle or atrioventricular bundle, it transmits the electrical impulses from the AV node to apex. Cell permeability is the ability of cells to passage of substances through membranes. Purkinje fibres are specialized myocardial fibres that conduct an electrical stimulus or impulse through the heart. Great vessels is a term used to refer collectively to the four large vessels that bring

blood to and from the heart. *Pericardium* is a double-walled sac that contains the heart and the roots of the great vessels. *Endocardium* is the innermost layer of the heart. *Myocardium* is the middle layer of the walls of the heart.

1.2 Scope and Proposes

The purpose of this work is to explore the potentialities of adaptive signal processing for ECG denoising. The main objective is to understand how adaptive filter works, and study the performance of this technique in biological signal denoising. The main activities to accomplish this task are the following:

- Two ECG signals from different sources will be considered in this work, intending to grasp the efficiency of denoising process for high and low quality ECG signals. One ECG signal is a high resolution record from Massachusetts Institute of Technology Beth Israel Hospital database (MIT-BIH), and the other signal is from a human volunteer captured with a low cost electrocardiograph.
- The noises under consideration will be electromyography and power line noises.
 These are the more common noises in ECG recordings. As for ECG signal, will be considered simulated and real noise signals, where in denoising process will be compared the denoising performance for simulated noises against real noises.
- The adaptive algorithms used in denoising process should tack into account low computational resources and considerable efficiency. For the case, it will be studied a recursive algorithm used for adaptive filter named LMS algorithm. This algorithm offers slow computational requirements and high efficiency.
- It is also considered FIR filtering for same signal and noises, aiming to realise the differences between both techniques.

1.3 Outline of the Thesis

This thesis is organized as follows:

Chapter 2 introduces the basic concepts of anatomy and physiology of the heart. The anatomy is concerned to anatomic structures, and physiology intends to explain the physical and chemical factors that are responsible for the heart function.

Chapter 3 describes the methods used for recording electrocardiograms and the

respective equipment and electrodes. In this chapter it is also referred the Holter system for long term ECG recording.

Chapter 4 presents the noise properties and characteristics, as well as the most common noise sources associated to ECG. This chapter also presents a literature review about the methodologies used to ECG signal denoising.

Chapter 5 introduces the basic concepts of Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) digital filters, and the adaptive signal processing schemes for signal denoising based on FIR filters. In this chapter, it is also discussed several aspects about the LMS algorithm.

Chapter 6 exposes the implementation procedures, the tests and the respective results.

Chapter 7 summarizes the main conclusions and discusses future work.

2

Anatomy and Physiology of the Heart

The function of the heart is pumping the blood into the circulation system to service the needs of the body tissues. The heart is the most important muscle in the body, it can beat more than 100.000 times a day and pumping around 7000 litres of blood every day.

This chapter will present a short resume of anatomic and physiologic functions of the human heart, where the contents are based on literature resume of [6]. The chapter will start with a description of heart muscular characteristics, and the respective characteristics of the four major chambers. Then will be described some aspects related with the special mechanisms for transmitting action potentials throughout the heart muscle that cause the continuing succession of heart contractions. The remaining sections of this chapter describe the ECG generation, from action potentials to normal ECG waveform.

2.1 Heart Muscle

The human heart has four major chambers pumps disposed as shown in Figure 2.1. These four major chambers are: right atrium; right ventricle; left atrium and left ventricle.

Each pair of chambers is divided by cardiac valves, used to block the blood flow during the heart pumping. The tricuspid valve prevents the blood flow between left ventricle and left atrium; the mitral valve has the same function on the right side. The heart has a ortic valve and pulmonary valve to prevent blood reflow from a orta and pulmonary arteries respectively.

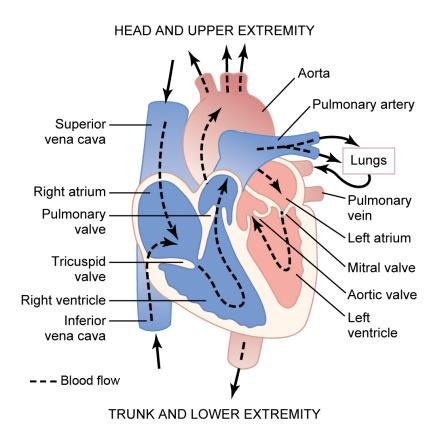


Figure 2.1: Structure of the heart, and course of blood flow through the heart chambers and heart valves[6].

The upper side of heart has the superior vena cava and aorta. The superior vena cava receives venous blood from upper side of the body, and aorta supplies this same region of the body. The lower side of the heart has the inferior vena cava that receives venous blood from lower side of the body, and the aorta to supply blood for this region of the body. Lungs are connected between pulmonary arteries and pulmonary veins.

The muscular tissue structure of the heart, is known as myocardium, it is the middle layer of the heart walls. The innermost layer of tissue, is called endocardium, and the muscular barrier that separate the left and right ventricles is named ventricular septum. Externally, heart is protected by the pericardium, which is a "bag" that contains the heart and the roots of the superior vena cava, inferior vena cava, pul-

monary artery and aorta¹.

Human heart is composed by three major types of cardiac muscles: atrial muscle fibres, ventricular muscle fibres, and specialized excitatory and conductive muscle fibres. The characteristics of these muscular fibres, accomplish different requirements in the heart pumping system. Atrial and ventricular muscles fibres contract in much the same way as skeletal muscle, except that the duration of contraction is much longer in the heart. Conversely, the specialized excitatory and conductive fibres have a softly contract, because they contain only a few contractile fibres. Instead, they exhibit either automatic rhythmical electrical discharge in the form of action potentials or conduction of the action potentials through the heart, providing an excitatory system that controls the rhythmical beating of the heart.

2.1.1 The Special Heart Transmission Fibres

The special heart transmission fibres are located in the inner ventricular walls of the heart, just below the endocardium, as shown in Figure 2.2 a). These special fibres conducing the electrical stimulus or impulses through heart tissues. The Sinoatrial (SA) node located in the right atrium of the heart, is the impulse generator, and thus the generator of normal sinus rhythm. In parallel, the signal travels to the Atrioventricular (AV) node via internodal pathways.

2.1.2 Distribution of the Purkinje Fibres in the Ventricles

The fibres fom the AV node to the end of ventricles are the *Purkinje fibres*. They consist into AV bundle² and left and right bundle branches. Each branch spreads downward toward the apex of the ventricle, progressively dividing into smaller branches.

An important aspect is that AV bundle has a special characteristic; it is the inability, of action potentials to travel backward from the ventricles to the atria. This effect is commonly called *One-Way Conduction*, Figure 2.2 b) shows an detailed image of this area. This characteristic prevents re-entry of cardiac impulses, by this route, from the ventricles to the atriums, allowing only forward conduction from the atriums to the ventricles.

¹This group of four vessels are commonly called as great vessels

²Also called bundle of His due to Wilhelm His, which was the first to describe them

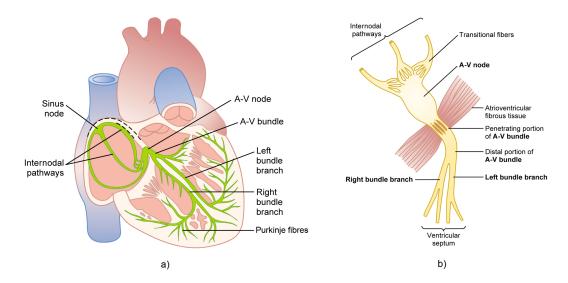


Figure 2.2: a) Sinus node, and the Purkinje system of the heart, showing also the AV node, atrial inter-nodal pathways, and ventricular bundle branches. b) Organization of the AV node[6].

2.2 Heart Physiology

The rate of blood that flows through human body tissues is controlled in response to tissues needed for nutrients. Therefore, the heart and circulation are dynamically controlled by the autonomic nervous system, which automatically control de heart rate. The details of circulatory function are complex but, in summary, the needs of the individual tissues are served specifically by bload circulation, where the heart is the main pump of the system. Figure 2.3 resumes the blood circulation and division of blood, in percentage, into the systemic circulation and the pulmonary circulation. The systemic circulation, also called the greater circulation or peripheral circulation, is responsible to supplies blood to all the tissues in the body except the lungs, and pulmonary circulation with respect to lungs.

Each atrium is a weak primer pump for the ventricle, helping blood flow into the ventricle. The right atrium receives the blood poor in oxygen from the body and delivery it to right ventricle. Then, the right ventricle pumps the blood through the pulmonary artery into the lungs, were will became oxygenated. The left side receives this rich oxygenated blood from the lungs and then pumps the blood through the aorta back to the rest of the body. In resume, the right side of the heart pumps blood through the lungs, and left side pumps blood through the peripheral organs. It is clear that the ventricles supply the main pumping force that propels the blood through the pulmonary circulation and through the peripheral circulation. Due to

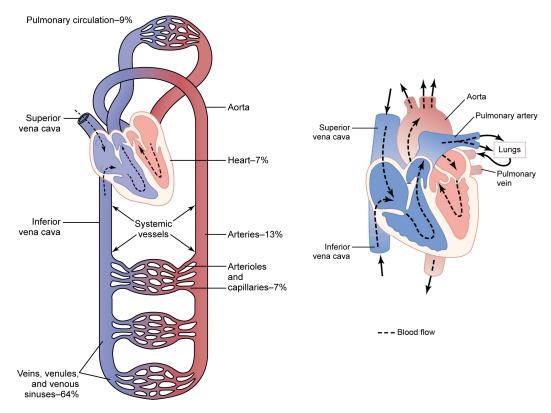


Figure 2.3: Distribution of blood (in percentage of total blood) in the different parts of the circulatory system [6].

the higher requirement of pressure to supplies the systemic circulation, left ventricle has more muscular tissue than right ventricle.

2.2.1 Regulation of Heart Pumping

It was referred that the function of the heart is pumping the blood into the circulation system to service the needs of the body tissues. When a person is resting the heart pumps only 4 to 6 litres of blood each minute, but if in severe exercise, the heart may be required to pump four to seven times this amount.

Under most conditions, the amount of blood pumped by the heart each minute is determined almost entirely by the rate of blood flow into the heart from the veins, which is called venous return, *i.e.* the blood that refill the right atrium. That is, each peripheral tissue of the body controls its own local blood flow. The heart, in turn, automatically pumps this incoming blood into the arteries, so that it can flow around the circuit again.

When an extra amount of blood flows into the ventricles, the cardiac muscle itself is stretched to greater length. Because of this increased pumping, the ventricles

automatically pump the extra blood into the arteries.

2.3 Action Potentials

Cardiac cells, and all living cells in the body, have an electrical potential across the cell membrane. Figure 2.4 shows a cell membrane, where many ions have a concentration gradient across the membrane, including potassium (K+), with high concentration inside the cell (intracellular) and a low concentration outside (extracellular) the membrane. Sodium (Na+) and chloride (Cl-) ions are at high concentrations in the extracellular region, and low concentations in the intracellular regions. This voltage is established when the membrane has permeability to one or more ions.

In the example of Figure 2.4, if the membrane has selective permeability to po-

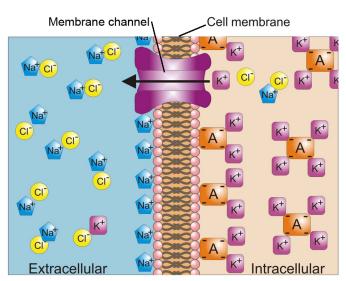


Figure 2.4: Membrane potential is the difference in electrical potential between the interior and exterior of a biological cell Adp. [7].

tassium, these positive charged ions can diffuse through the membrane channel to the outside of the cell, leaving behind uncompensated negative charges. This charges separation is what causes the membrane potential. This potential can be measured by inserting a microelectrode into the cell and measuring the electrical potential, in millivolts (mV), inside the cell relative to the outside of the cell³. The voltage across the membrane, ranges from about - 50 to - 200 millivolts, where the minus sign indicates that inside of the cell is negative relative to outside[8]. Human heart has three types of membrane ion channels:

1. fast sodium channels,

³By convention, the outside of the cell is considered 0 mV.

- 2. slow sodiumcalcium channels,
- 3. potassium channels.

These channels will control the speed that signal travels through cardiac muscle, due to the permeability to ions such as sodium and potassium.

When the membrane potential suddenly depolarizes and then repolarizes back to its resting state, produces the voltage shape represented in Figure 2.5a), which is called Action Potential. When compared, it is possible to see a swing of about 100 mV between the resting and excited state. Initially the potential has a baseline voltage (B) near to -80 mV. During excitation (E), the membrane permeability change, and signal rises abruptly. This is due to rapid influx of positive sodium ions to the interior of the fibre. After this peak overshoot, at about +20 mV, the potential maintains a plateau voltage (P) near to -20 mV during around 300 ms, caused primarily by slower opening of the slow sodium-calcium channels. Finally, potassium channels opens and allows diffusion of large amounts of positive potassium ions in the outward direction through the fibre membrane and returns the membrane potential to its resting level (R). The overall action potential duration is about 400 ms[9].

The voltage shape of action potentials depends on the type of fibres, and in Figure

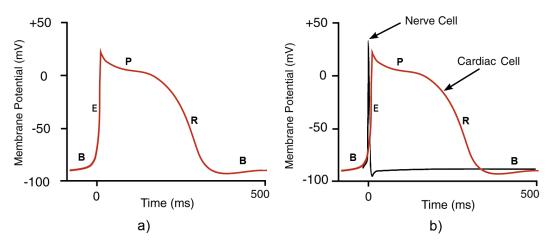


Figure 2.5: a) Cardiac action potential, B is the baseline; E corresponds to excitation; R corresponds to recovery (repolarization) and P is the plateau. B) Comparison of action potentials and nerve cell action potentials Adp. [2, 9].

2.5b) it is shown a comparison between heart cells action potentials and nerve cells action potentials, where cardiac action potentials are much longer in duration than nerve cell action potentials. Therefore, depending on the differences between heart fibres, the signal produced is different as well. Figure 2.6 shows some examples of different shapes in different places of the heart. The summation of all action potentials will produce the ECG waveform.

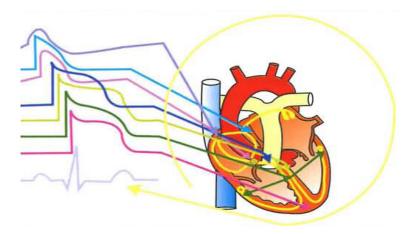


Figure 2.6: Action potential waveforms and propagation in the human heart[10].

Figure 2.7 is an example of the relation between the ventricular muscle action potential and QRS and T Waves for a normal ECG. Signal from Figure 2.7a) is captured inside of a single ventricular muscle fibre. It is possible to see in Figure 2.7b) that QRS waves appearing at the beginning of the monophasic action potential and the T wave appearing at the end. This also shows that no potential is recorded in the electrocardiogram when the ventricular muscle is either completely polarized or completely depolarized. Therefore, we only have the possibility to record ECG signals when the ionic current flows from one part to another part in heart, resulting in electrical current flowing to the surface of body producing the ECG signal.

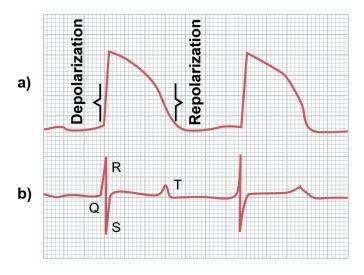


Figure 2.7: Monophasic action potential and Electrocardiogram recorded simultaneously[6].

2.3.1 Cardiac Impulse Transmission

The cardiac impulse will dictates de heart electrical function. Figure 2.8, shows in summary, the transmission times of the cardiac impulse through the human heart. The numbers on the figure represent the intervals of time in fractions of seconds.

The SA node is the electrical source, where it is produced the impulse to control the

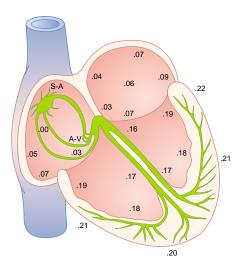


Figure 2.8: Transmission of the cardiac impulse through the heart, showing the time of appearance (in fractions of a second after initial appearance at the sinoatrial node) in different parts of the heart/6

_

heart, *i.e.*, it is the pacemaker. Then, the numbers represent the time elapsed from signal generation to that point. With these values it is possible to realise the speed differences within the different cellular structures of the heart transmission fibres. For example, the velocity of the excitatory action potential signal along both atrial and ventricular muscle fibres is about 0.3 to 0.5 m/sec, which is about 1/10 of velocity in skeletal muscle fibres. Conversely, the Purkinje fibres allow speeds as great as 4 m/sec, where this rapid conduction of the excitatory signal is important to perform a fast delivery of signal to the different parts of the heart. Once the impulse reaches the ends of the Purkinje fibres, it is transmitted through the ventricular muscle mass by the ventricular muscle fibres themselves. The velocity of transmission is now only 0.3 to 0.5 m/sec, one sixth that in the Purkinje fibres.

2.4 The Normal Electrocardiogram

As cardiac cells depolarize and repolarize, electrical currents spread throughout the body because the tissues surrounding the heart are able to conduct this electrical

currents. When these electrical currents are measured by an array of electrodes placed at specific locations on the body surface, the recorded tracing is called an ECG. A normal ECG trace is represented in Figure 2.9, where P wave and the components of the QRS complex are depolarization waves and T wave is the repolarisation wave. P wave is caused by electrical potentials generated due to normal depolarization in the atriums immediately before their contractions. The ventricular depolarization occurs after atrial depolarization, which is represented by QRS complex. Finally, the heart re-establishes their potentials recovering from the state of depolarization. This recovering is known as repolarization, producing the T wave. This process occurs in a continuous way producing the hart-rate.

The PR interval represents the time required for the depolarization waves to trans-

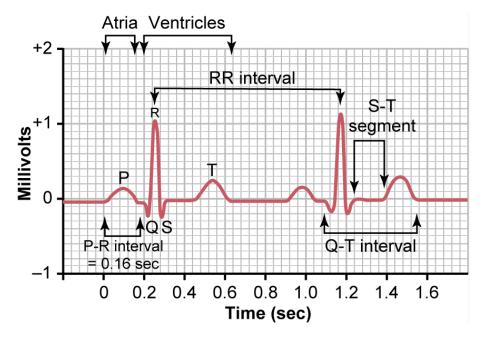


Figure 2.9: Normal electrocardiogram[6].

verse the atria and the atrioventricular node; the Q-T interval represents the period of ventricular depolarization and repolarisation; and the ST segment is the isoelectric period when the entire ventricle is depolarized.

The rate of heartbeat can be easily achieved from an electrocardiogram because the heart rate is the inverse of the time interval between two successive heartbeats. The normal interval between two successive QRS complexes (RR interval) in the adult person is about 0.83 second. This is a heart rate of 60/0.83 times per minute, or 72 beats per minute.

2.4.1 Voltage and Time of Electrocardiogram

All recordings of electrocardiograms are made with appropriate calibration lines on the recording paper. Either these calibration lines are already ruled on the paper, as is the case when a pen recorder is used, or they are recorded on the paper at the same time that the electrocardiogram is recorded, which is the case with the photographic types of electrocardiographs. As shown in Figure 2.9, the horizontal calibration lines are arranged so that 10 of the small line divisions upward or downward in the standard electrocardiogram represent 1 millivolt, with positive values in upward direction and negative values in downward direction. The vertical lines on the electrocardiogram are time calibration lines. Each five vertical segment lines represent 0.20 second. The 0.20 second intervals are then broken into five smaller intervals by thin lines, therefore, each of which represents 0.04 second.

When electrocardiograms are recorded from electrodes on the two arms or on one arm and one leg, the voltage of the QRS complex usually is 1.0 to 1.5 millivolt from the top of the R wave to the bottom of the S wave; the voltage of the P wave is between 0.1 and 0.3 millivolt; and the T wave is between 0.2 and 0.3 millivolt. Moreover, the wave recorded voltages in the normal electrocardiogram depend on the manner in which the electrodes are applied to the surface of the body and how close the electrodes are to heart. If one electrode is placed directly over the ventricles and a second electrode is placed far away from the heart, the voltage of QRS complex may be as great as 3 to 4 millivolts. Even this voltage is small in comparison with the monophasic action potentials recorded directly at the heart muscle membrane. The summary for a normal ECG waves, intervals, and segments are shown in Table 2.1.

Table 2.1: Summary of ECG Waves, Intervals, and Segments [2]

ECG Component	Represents	Duration (sec)
P wave	Atrial depolarization	0.08 - 0.10
QRS complex	Ventricular depolarization	0.06 - 0.10
T wave	Ventricular repolarization	1
P-R interval	Atrial depolarization plus AV nodal delay	0.12 - 0.20
ST segment	Isoelectric period of depolarized ventricles	1
Q-T interval	Length of depolarization plus repolarization -	$0.20 - 0.40^2$
	corresponds to action potential duration	

¹Duration not normally measured.

²High heart rates reduce the action potential duration and therefore the Q-T interval.

2.4.2 The Cardiac Cycle

As referred in section 2.4, through RR interval it is possible to achieve the heart rate. The successive heart contractions forced by SA node is called *Cardiac Cycle*. Several events can be observed during the cardiac cycle, Figure 2.10 shows the

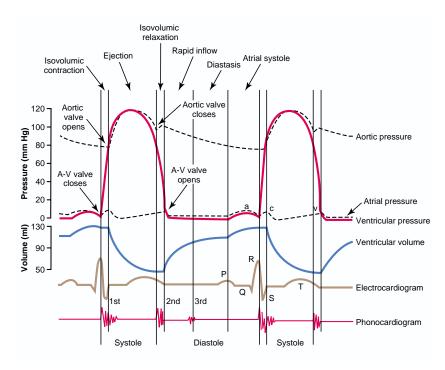


Figure 2.10: Events of the cardiac cycle for left ventricular function, showing changes in left atrial pressure, left ventricular pressure, aortic pressure, ventricular volume, the electrocardiogram, and the phonocardiogram [6].

different events during this cycle for the left side of the heart. The cardiac cycle consists of a period of relaxation called diastole, during which the heart fills with blood, followed by a period of contraction called systole. The top three curves of this figure shows the pressure changes in the aorta, left ventricle, and left atrium, respectively. The fourth curve depicts the changes in left ventricular volume, the fifth the electrocardiogram, and the sixth a Phonocardiogram (PCG)⁴.

It is important to refer that a few other parts of the heart can exhibit intrinsic rhythmical excitation in the same way that the sinus nodal fibres. This is the case of AV nodal and Purkinje fibres! Without outside excitation, the AV nodal fibres discharge at an intrinsic rhythmical rate of 40 to 60 times per minute, and the Purkinje fibres discharge at a rate somewhere between 15 and 40 times per minute. This

⁴A Phonocardiogram is a plot of sounds made by the heart during a cardiac cycle.

time differences leads to each time the sinus node discharges, its impulse will discharges both the AV node and the Purkinje fibres, before self-excitation can occur in either of these. Thus, the sinus node controls the beat of the heart because its rate of rhythmical discharge is faster than any other part of the heart.

The rhythmical and conductive system of the heart is susceptible to damage by heart disease, especially by ischemia of the heart tissues resulting from poor coronary blood flow. The result is often a bizarre heart rhythm or abnormal sequence of contraction of the heart chambers, and the pumping effectiveness of the heart often is affected severely, even to the extent of causing death.

3

Electrocardiography

Electrocardiography is the interpretation of electrical activity of the heart over a period of time, which produces a representation of ECG. The ECG is a crucial diagnostic tool in clinical practice. It is especially useful in diagnosing rhythm disturbances, changes in electrical conduction, and myocardial ischemia and infarction. In noninvasive electrocardiography, the signal is detected by electrodes attached to the outer surface of the skin and recorded by a device external to the body. The sections of this chapter describe the methods used for recording Electrocardiograms. The locals of electrodes and the respective signal associated to those locals. Then will be presented a brief exposition about the instrumentation used in ECG field.

3.1 Methods for Recording Electrocardiograms

The ECG is recorded by placing an array of electrodes at specific locations on the body surface. This is possible because the heart is suspended in a conductive medium. Figure 3.1 shows the ventricular muscle within the chest. When one portion of the ventricles depolarizes and therefore becomes negative with respect to the remainder parts of the heart, forming a potential difference. The electrical currents flow from the depolarized area to the polarized area in large circuitous routes.

It is this electrical field that can be collected under surface of the heart. In fact, this is the summation of all action potentials mentioned in section 2.3.

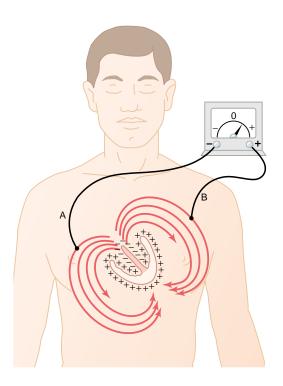


Figure 3.1: Flow of current in the chest around partially depolarized ventricles[6].

3.1.1 Electrocardiographic Leads

Conventionally, electrodes are placed on each arm and leg, and six electrodes are placed at defined locations on the chest. Three basic types of ECG leads are recorded by these set of electrodes: standard bipolar limb leads, chest leads and augmented limb leads. The limb leads are referred as bipolar leads because each lead uses a single pair of positive and negative electrodes. The augmented leads and chest leads are unipolar leads because they have a single positive electrode with other electrodes coupled together electrically to serve as a common negative electrode.

Three Bipolar Limb Leads

Figure 3.2 shows electrical connections between the patient limbs and the electrocardiograph for recording electrocardiograms from the so-called standard bipolar limb leads. In these arrangements the electrocardiogram is recorded from two electrodes located on different sides of the heart, in this case, on the limbs. Three different connections are possible, Lead I, Lead II and Lead III.

Lead I In recording limb Lead I, the negative terminal of the electrocardiograph is connected to the right arm and the positive terminal to the left arm. Therefore,

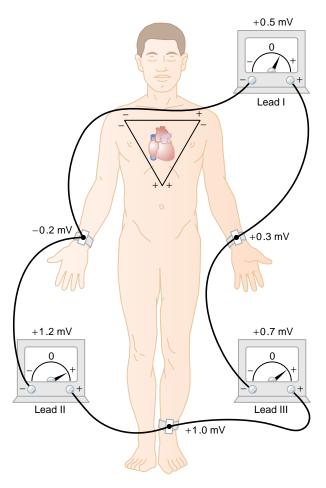


Figure 3.2: Conventional arrangement of electrodes for recording the standard electrocardiographic leads. Einthoven's triangle is superimposed on the chest[6].

the electrode of the right arm is electronegative with respect to the electrode of the left arm. The electrocardiograph records a positive signal, that is, above the zero voltage reference line in the electrocardiogram. When the opposite is true, the electrocardiograph records below this line.

Lead II To record limb lead II, the negative terminal of the electrocardiograph is connected to the right arm and the positive terminal to the left leg. Therefore, when the right arm is negative with respect to the left leg, the electrocardiograph records positively.

Lead III To record limb lead III, the negative terminal of the electrocardiograph is connected to the left arm and the positive terminal to the left leg. This means that the electrocardiograph records a positive signal when the left arm is negative with respect to the left leg.

These three limb leads roughly form an equilateral triangle with the heart at the

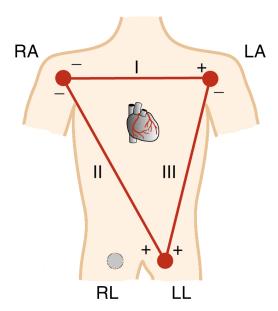


Figure 3.3: Einthoven Triangle with the placement of the standard ECG limb leads and the location of the positive and negative recording electrodes for each of the three leads. RA, right arm; LA, left arm; RL, right leg; LL, left leg Adp. [2].

center, refer to Figure 3.3. This triangle is called Einthoven's triangle in respect of Willem Einthoven who developed the ECG in 1901. The two vertices at the upper part of the triangle represent the points at which the two arms are electrically connected, and the lower vertex is the electrode located on the right leg used as a ground point.

Depending on the lead used to record the ECG signal, the resultant shape is slightly different, this differences can be observed in Figure 3.4.

In the three electrocardiograms represented in Figure 3.4, it can be seen, that at any given instant the sum of the potentials in leads I and III equals the potential in lead II, thus illustrating the validity of Einthoven's law.

The signals from these leads are identical between them, it does not matter greatly which lead is recorded when one wants to diagnose different cardiac arrhythmias, because diagnosis of arrhythmias depends mainly on the time relations between the different waves of the cardiac cycle.



Figure 3.4: Normal electrocardiograms recorded from the three standard electrocardiographic leads[6].

Chest Leads

When it is important to diagnose damages in the ventricular or atrial muscles, or in the Purkinje conducting system, the three Bipolar Limb Leads records are not useful. For these cases, we need leads that can show the abnormalities of cardiac muscle contraction or cardiac impulse conduction in these areas. The preferred leads for diagnose these cases are the chest leads, also called Precordial Leads, which are represented in Figure 3.5. These leads are used to record ECG with one electrode placed on the anterior surface of the chest directly over the heart at one of the points shown in Figure 3.5. The different recordings are known as leads V₁, V₂, V₃, V₄, V₅, and V₆. This electrode is connected to the positive terminal of the electrocardiograph, and the negative electrode, called the indifferent electrode, is connected through equal electrical resistances to the right arm, left arm, and left leg, all at the same time. Usually these six standard chest leads are recorded, one at a time, where the chest electrode is being placed sequentially at the six points shown in the figure.

Figure 3.6 illustrates the electrocardiograms of the healthy heart as recorded from these six standard chest leads. Each chest lead records mainly the electrical potential of the cardiac musculature immediately beneath the electrode, because the heart surfaces are close to the chest wall. Therefore, relatively minute abnormalities in the ventricles, particularly in the anterior ventricular wall, can cause marked changes in the electrocardiograms recorded from individual chest leads.

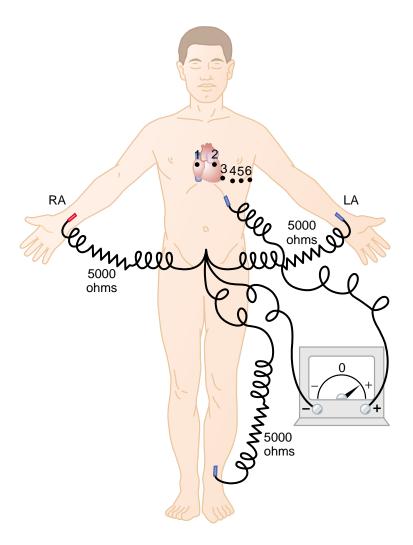


Figure 3.5: Connections of the body with the electrocardiograph for recording chest leads. LA, left arm; RA, right arm[6].

Augmented Unipolar Limb Leads

Another system of leads in wide use is the augmented unipolar limb lead. In this type of recording, two of the limbs are connected through electrical resistances to the negative terminal of the electrocardiograph, and the third limb is connected to the positive terminal. When the positive terminal is on the right arm, the lead is known as the aVR lead; when on the left arm, the aVL lead; and when on the left leg, the aVF lead. Figure 3.7 showns the angular position of these leads in respect to bipolar limb leads. The normal recordings of this arrangement are shown in Figure 3.8. They are all similar to the standard limb lead recordings, except that the recording from the aVR lead is inverted due to the polarity connections to the

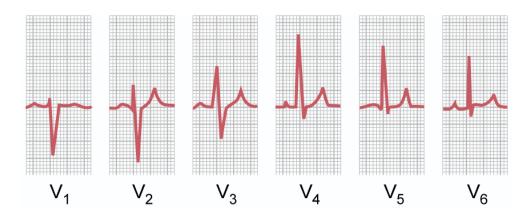


Figure 3.6: Normal electrocardiograms recorded from the six standard chest leads[6].

electrocardiograph.

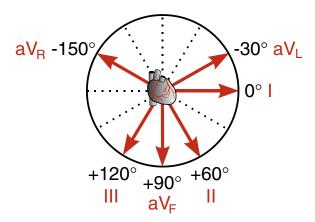


Figure 3.7: The angular position of Augmented Unipolar Limb Leads in respect to Bipolar Limb Leads[2].

3.2 ECG Instrumentation

The electrical activity of the heart is fairly simple to measure. In the very early 1900s, Willem Einthoven won the Nobel Prize in medicine for his work identifying and recording the parts of the electrocardiogram. Figure 3.9b) shows a photography of Willem Einthoven and Figure 3.9a) a photography of its complete electrocardiograph machine with a patient. Today's medical instruments are considerably more complicated and diverse, mainly because they incorporate electronic systems for sense, manipulate, store, and display data and information. Today, an electrocardiograph is more compact and offers several functionalities, e.g. the model PageWriter

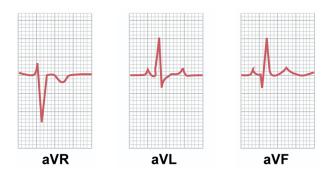


Figure 3.8: Normal electrocardiograms recorded from the three augmented unipolar limb leads [6].

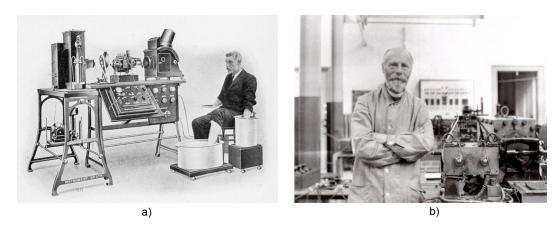


Figure 3.9: a) Photograph of a complete electrocardiograph, showing the manner in which the electrodes are attached to patient, in this case the hands and one foot being immersed in jars of salt solution. b) Willem Einthoven in the lab.

TC70 from Philips shown in Figure 3.10a) offers the possibility to record 20 minutes of up to 16 leads simultaneously, into a box of $40 \times 33 \times 16$ cm. In Figure 3.10b) it is shown the model StressVue from same supplier used for stress ECG recordings, for example during an exercise.

Mostly of these equipments are considered High Resolution ECG (HRECG) systems, where at least three bipolar leads are used in an anatomic xyz coordinate system.

3.2.1 The Ambulatory ECG

Due to their complexity, medical ECG equipments are used mostly in hospitals and medical centres by trained personnel, but some also can be found in private homes operated by patients themselves or their caregivers. Examples of these equipments are the portable devices for personal usage and long term recorders called Holter



Figure 3.10: a) Philips electrocardiograph model PageWriter TC70. b) Philips stress testing system StressVue.

devices. The original large-scale clinical use of this technology was to identify patients who developed heart block transiently and could be treated by implanting a cardiac pacemaker. The very first device was developed by Dr. Norman Jeff Holter in the early 1940s, refer to Figure 3.11a), where the data is recorded into a tape and the weight of this equipment surrounds 38 Kg, Figure 3.11b) shows a patient holding the Holter monitor[11]. The evolution of Holter ECG is closely followed by technical

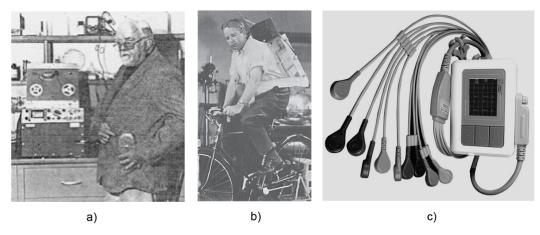


Figure 3.11: a) Dr. Norman Jeff Holter (1914-1983) with original Holter; b) A patient with the original Holter device from 1947; c) Low cost modern Holter model MIC-12H-3L from Beijing Jinco Medical.

and clinical progress. A modern Holter device can record tree to twelve simultaneous leads from 24 to 48 hours into a digital memory. Figure 3.11c) shows an example of a low cost modern Holter model MIC-12H-3L from Beijing Jinco Medical, with

ability to record twelve leads during 24 hours.

3.2.2 Electrocardiograph Block diagram

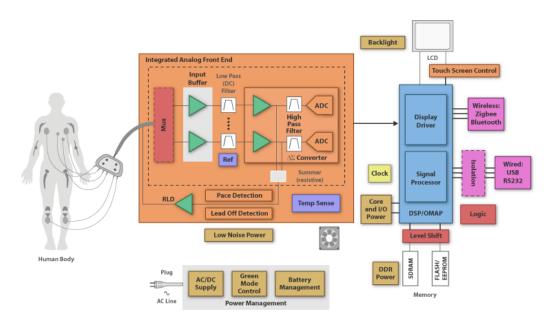


Figure 3.12: ECG system block diagram[12].

Figure 3.12 shows the block diagram of an ECG system. Basic functions of an ECG machine include: ECG waveform display, either through Liquid Crystal Display (LCD) screen or printed paper media, and heart rhythm indication as well as simple user interface through buttons. More features, such as patient record storage through convenient media, wireless/wired transfer and 2D/3D display on large LCD screen with touch screen capabilities, are required in more and more ECG products. Multiple levels of diagnostic capabilities are also assisting doctors and people without specific ECG trainings to understand ECG patterns and their indication of a certain heart condition. After the ECG signal is captured and digitized, it will be sent for display and analysis, which involves further signal processing[12].

3.3 ECG Electrods

The measurements of electrical activity in the heart, muscles, or brain are examples of direct measurements of physiological energy. For these measurements, the energy is already electrical and only needs to be converted from ionic to electronic current using an electrode. To collect ECG at surface of skin, it is indispensable the use of electrodes, and the electrodes used by non-evasive electrocardiography are so many

that will be only covered here their principal aspects.

The electric characteristics of bio-potential electrodes are generally nonlinear and a function of the current density at their surface. But electrodes are usually represented by linear models due to they operation at low potentials and currents[13, 14, 15, 16]. Under these conditions, electrodes and the skin model can be represented by the equivalent circuit shown in Figure 3.13. In this circuit R_P and C_P are components

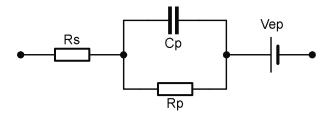


Figure 3.13: Liner model of an electrical equivalent circuit for a bio-potential electrode.

that represent the impedance associated with the electrode-electrolyte interface and polarization at this interface. R_s is the series resistance associated with interfacial effects and the resistance of the electrode materials themselves, and V_{ep} represents the half-cell potential. Half-cell potential is associated to the distribution of ions or charged molecules in a biologic structure. The half-cell potential occurs due to the interaction between the metal of the electrode and the solution used near to the metal surface. The use of this solution is crucial for better adapting the contact between the electrodes and the skin. In fact, when the cations in this solution and the metal of the electrodes are the same, the half-cell potential is reduced[17, 18]. The values of these potentials are dependent of the characteristics of materials and can be described by the Nernst:

$$V_{ep} = -\frac{GT}{nF} \ln Q \tag{3.1}$$

Where T is the absolute temperature (Kelvin), $G = 8.31451 Jmol^{-1}K^{-1}$) is the ideal gas constant, $F = 96485.3 Cmol^{-1}$ is Faraday's constant, and n is the number or electrons transferred in the balanced oxidation/reduction reaction, and Q is the reaction quotient, *i.e.* the extracellular and intracellular concentrations.

 V_{ep} value is the value corresponding to materials/reactions $Ag + Cl^- \rightarrow AgCl + e^- = +0.223V$. This constant is based on the assumption that electrode distance between metal and skin is constant. If this distance changes V_{ep} take much higher values, which is described as motion artefacts¹. The most important aspect is that the presence of the electrode does not affect the variable being measured.

¹Motion artefacts are a typical noise associated to movements of electrodes in the skin.

Depending on the type of ECG that are being measured, different electrodes

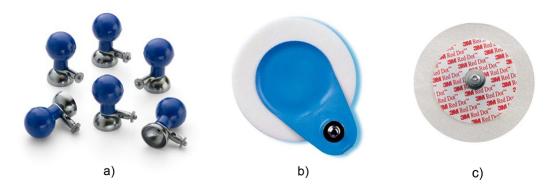


Figure 3.14: ECG electrodes: a) electrodes for diagnostic resting, b) electrodes for stress test and Holter, c) electrodes for monitoring.

should be used. In the market it is possible to find different types of electrodes, but they mainly occupy three different families: electrodes for diagnostic resting ECG, Figure 3.14a); electrodes for stress test and Holter ECG, Figure 3.14b); electrodes for monitoring ECG, Figure 3.14c).

4

Noise

Noise is present in almost all environments, and can be defined as an undesirable signal that interferes with the desired signal. A noise itself is a signal that can be generated from several sources, and takes different spectrum distributions. In fact, biomedical electrical signals, which are the scope of this work, are always polluted with some kind of noise. These interference signals includes interferences from power supplies, motion artefacts due to patient movement, radio frequency interference, defibrillation pulses, pace maker pulses, interferences from other monitoring equipment, etc[12]. The big challenge of noise in biomedical signals is closely related with amplitude of the desired signals face to the noise, i.e. the Signal-to-Noise Ratio (SNR). For instance, an ECG measurement gets challenging due to the presence of the large DC offset and various interference signals. This potential can be up to 300 mV for a typical electrode, which is several times larger than ECG signal. Noise reduction is an important task to solve in biomedical signals and for this reason, the understanding of noise characteristics is the focus of the contents in this chapter. The chapter will starts with noise properties and characteristics as SNR and separability, followed by most common noises sources associated to ECG. Finally it is presented the literature review about the methodologies used to ECG signal denoising.

4.1 Noise Properties

Depending on its frequency or time characteristics, a noise process can be classified in several categories: Narrowband noise, White noise, Band-limited white noise, Coloured noise, Impulsive noise and Transient noise pulses[19]. Narrowband noise is a noise process with a narrow bandwidth such as a 50Hz hum from the power lines. White noise is purely random noise that has a flat power spectrum. White noise theoretically contains all frequencies in equal intensity. Band-limited white noise it is a noise with flat spectrum and limited bandwidth that usually covers the limited spectrum of the device or the signal of interest. Coloured noise it is non-white noise or any wideband noise whose spectrum has a non-flat shape; examples are pink noise, brown noise and autoregressive noise. Impulsive noise consists of short-duration pulses of random amplitude and random duration. And transient noise pulses consists of relatively long duration noise pulses.

4.1.1 Noise Characteristics

Noise is usually represented as a random variable, x(n), and describing his properties as a function of time it is not very useful. Therefore, it is more common the evaluation of its probability distribution, range of variability, or frequency characteristics[20]. While noise can take a variety of different probability distributions, the *Central Limit Theorem*¹ implies that noises will have a Gaussian or normal distribution. The probability p(x) of a Gaussianly distributed variable, x, is specified by the normal or Gaussian distribution equation:

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(x-a)^2}{2\sigma^2}}$$
(4.1)

Where, a it is the *mean*, or average value, and σ^2 is the *variance*. The arithmetic quantities of mean and variance are frequently used in signal processing algorithms. The mean value of a discrete array of N samples is evaluated as:

$$\overline{x} = \frac{1}{N} \sum_{k=1}^{N} x_k \tag{4.2}$$

¹The central limit theorem explains why many distributions tend to be close to the normal distribution, *i.e.*, when noise is generated by a large number of independent sources it will have a Gaussian probability distribution.

And the variance, σ^2 , is calculated as:

$$\sigma^2 = \frac{1}{N-1} \sum_{k=1}^{N} (x_k - \overline{x})^2 \tag{4.3}$$

From Equation (4.3) we grasp the standard deviation σ , which is just the square root of the variance.

Normalizing Equation (4.3) by:

$$\frac{1}{N-1} \tag{4.4}$$

will produces the best estimate of the variance if x is a sample from a Gaussian distribution. Alternatively, normalizing the Equation (4.3) by:

$$\frac{1}{N} \tag{4.5}$$

produces the second moment of the data around x, which is equivalent to RMS value of the data if the data have zero as mean value.

If noise is captured from different sensors, such as sensor array, or multiple observations from the same source, the standard deviation of noise becomes reduced by the square root of the number of averages.

4.1.2 Signal-to-Noise Ratio

From previous notes at beginning of this chapter, signal and noise are relative terms: general speaking, signal is the waveform of interest while noise is everything else. The relative amount of signal and noise present in a waveform is usually quantified by the SNR. As the name implies, this is simply the ratio of signal to noise, both measured in Root-Mean-Squared (RMS) amplitude. The SNR is often expressed in decibel (dB) where:

$$SNR = 20log \frac{Signal}{Noise} \tag{4.6}$$

To convert from dB scale to a linear scale:

$$SNR_{linear} = 10^{\frac{dB}{20}} \tag{4.7}$$

For example, a ratio of 20 dB means that the RMS value of the signal was 10 times the RMS value of the noise, because $10^{20/20} = 10$. A common value in this area is +3 dB, which indicates a ratio of $10^{3/20} = 1.414$, and -3 dB means that the ratio is 1/1.414. If noise and signal has the same amount in RMS value, this means 0 dB.

As an example, Figure 4.1 shows an ECG signal with different amounts of white noise. Notice that it is very difficult to detect presence of ECG signal visually when the SNR is -3 dB, and impossible when the SNR is -10 dB.

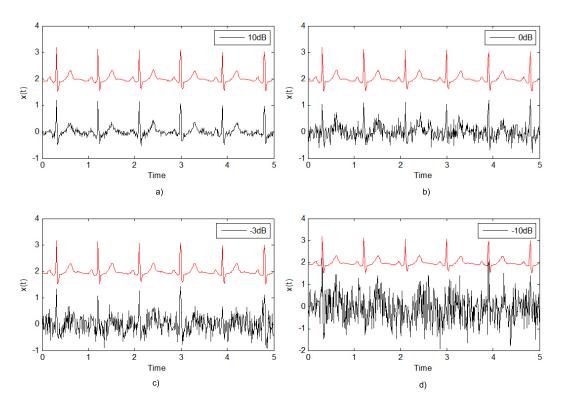


Figure 4.1: A ECG signal with varying amounts of added noise. The signal is barely discernable when the SNR is -3 dB and not visible when the SNR is -10 dB.

4.1.3 Separability of Signal and Noise

A signal is completely recoverable from noise if the spectra of the signal and the noise do not overlap. An example of a noisy signal with separable signal and noise spectra is shown in Figure 4.2(a). In this case, the signal and noise are placed in different parts of the frequency spectrum, and signal can be denoised with a low-pass filter. Although, Figure 4.2(b) illustrates a more common example of signal and noise, with overlapping spectra. For these cases, it is not possible to completely separate the signal from the noise; however, the effects of the noise can be more or less reduced depending on the filter technique used.

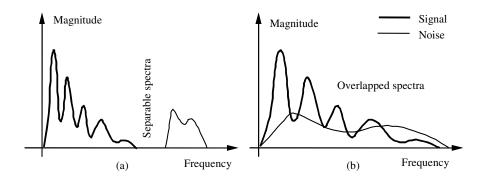


Figure 4.2: Illustration of separability: (a) The signal and noise spectra do not overlap, and the signal can be recovered by a low-pass filter; (b) the signal and noise spectra overlap, and the noise can be reduced but not completely removed[19].

4.1.4 Noise Correlation

A important aspect that should be taken into account is how well one instantaneous value of noise correlates with the adjacent instantaneous values, *i.e.* how much one data point is correlated with its neighbours. Correlation is a statistical measurement of the relationship between two variables. The values of correlation are in a range of +1 to -1, where zero correlation means that there is no relationship between the variables; -1 means a perfect negative correlation; and +1 indicates a perfect positive correlation. Perfect negative correlation is when one variable goes up the other goes down, and perfect positive correlation is when both variables move in the same direction together. For complete random noise with flat distributions, the correlation is zero, and in practice, most electronic sources produce noise that is essentially white up to many megahertz[20]. But, after filtering process, it becomes band limited which is commonly referred as coloured noise². Coloured noise shows correlation between adjacent points, this correlation becomes much stronger as the bandwidth goes to more monochromatic.

Correlation is a very important aspect to keep in mind when applying the adapting filter techniques discussed in Chapter 5.

4.2 Noise Sources

The presence of noise is fulfilled in various degrees in almost all environments. The most known and common are: Acoustic Noise, that emanates from moving, vibrating, or colliding sources and is the most familiar type of noise present in everyday environments; Electromagnetic Noise, wich is present at all frequencies and in particular

²Like coloured light; it only contains energy at certain frequencies

at radio frequencies; *Processing Noise*, that results from the signal processing, *e.g.* quantisation noise in digital coding, or lost data packets in digital data communication systems.

4.2.1 Biomedical Noises Sources

Noise frequently is a limitation factor in the performance of medical instrumentation, producing variability. In biomedical measurements, variability has four different origins:

- 1. Physiological variability;
- 2. Transducer artifact;
- 3. Environmental noise or interference;
- 4. Electronic noise.

Physiological Variability Physiological variability is due to the presence of other sources of biological influences than those of interest. For example, assessment of respiratory function based on the measurement of blood pO_2^3 could be confounded with other physiological mechanisms that change blood $pO_2[20]$. Physiological variability can be a very difficult problem to solve, where to solve it, sometimes it is required information provided by different sources to help in validation.

Transducer Artefact Transducer artefact is produced when the transducer is the responsible to change the desired signal. For example, non-invasive recordings of electrical potentials using electrodes placed on the skin are sensitive to motion artefact.

Environmental Noise Environmental noise is generated from existing sources, either external or internal to the body. For example, in a fetal ECG recording, the fetal ECG is corrupted by the mother ECG. In these cases it is not possible to describe the specific characteristics of environmental noise.

Electronic Noise Electronic noise falls into two broad classes: thermal or Johnson noise⁴, and shot noise. The former is produced primarily in resistor or resistance materials while the latter is related to voltage barriers associated with semiconductors. Both sources produce noise with a broad range of frequencies often extending from DC to $10^{12} - 10^{13}$ Hz.

³Partial Pressures of O_2 .

⁴Statistical fluctuation of electric charge exists in all conductors, producing random variation of potential between the ends of the conductor[21].

4.3 ECG Noises Sources

ECG signals always have background noise associated, and noise sources are so many that noise reduction became an important frontend signal processing task for biomedical signals. The most common noises that usually should be considered are: Power line interference, muscular contraction (EMG), Instrumentation noise generated by electronic devices, Baseline drift and ECG amplitude modulation[22, 23]. Power line interference is a narrow-band noise centred at 50 Hz with a bandwidth of less than 1 Hz. This type of noise usually contains harmonics due to parasite currents through human body. Power line interference is relatively constant during the ECG measurement. Cables used in electrodes connections are another source of power line noise[24].

Muscular contractions produce artefacts within millivolts level potentials. This signal is normally transient bursts of zero mean band-limited Gaussian noise[22]. The worst case of muscular contractions interference is when the measurements are made at same time as muscular activity, *i.e.*, in sports or jobs with intense body activity. In these cases, the muscular amplitude signal can completely overlaps the ECG signals. Without muscular activity the noise produced can be negligible due to its insignificant amplitude.

Artefacts generated by electronic devices can produce several different interferences, conducing to unpredictable noise shapes, leading to complete signal distortion or equipment saturation. If they do not consider these situations, these artefacts could be considered similar to Gaussian noise.

Baseline drift and ECG amplitude modulation with respiration occurs during the breathing cycle. The amplitude of ECG signal varies mainly influenced by relative distance between heart and electrodes. This distance is increased when lungs fill and reduces at time of lungs become empty. The effect can be observed as a slow modulation of the ECG amplitude with same frequency as the breathing cycle. The amplitude of the ECG signal also varies by about 15% with respiration [25, 26, 27, 28].

In addition, physiological and environmental noise affects the ECG power spectrum. ECG power spectrum can provide useful information about heart condition, and if ECG signal is polluted with noise for overall spectrum, becomes difficult to aim this information with good accuracy. Figure 4.3 summarizes the relative power spectra of the ECG, QRS complexes, P and T waves, motion artefact, and muscle noise. This graph reveals that the ECG signal has their energy mainly concentrated in frequencies below than 25 Hz, where the QRS complex assumes the major area. Also

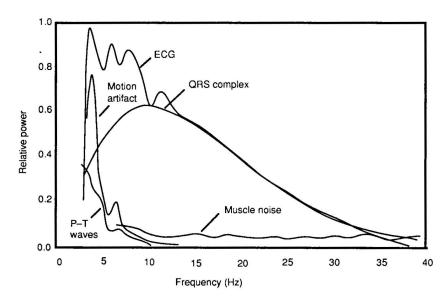


Figure 4.3: Relative power spectrum of QRS complex, P and T waves, muscle noise and motion artefacts based on an average of 150 beats[29].

shows that motion artefact overlapping a small part of ECG signal, and the EMG noise overlaps the entire ECG signal. It is clear that EMG noise can completely destroy ECG in a presence of low SNR.

4.4 ECG Noise Cancelation Techniques

Noise cancellation requires different strategies for different noise sources or types. Since the focus of this paper is a non classical method, the approaches covered in this section are all included in the non-classical methods used by several authors. An useful method for removing power line and baseline disturbances is the application of a digital linear phase filtering[30]. This method can be used to reduce signal magnitude spectrum while preserving the signal time domain as much as possible. The disadvantage of this method is the computational requirements. This is mainly caused by linear phase narrow-band filtering, that requires a long impulse response, and the corresponding number of filter coefficients caused by a large number of multiplications involved in the time domain[31].

Random and stationary noise can be removed using a temporal averaging method. Noise reduction by temporal averaging method is proportional to the square root of the number of frames or beats taken into the average[32]. This method only offers effective performance if a large number of samples is used. Moreover, due to heartbeats variability, it can cause considerable errors, producing distorted results, or extremely smooth waves.

To increase signal quality, some authors refer the performance of spatial averaging [33, 34, 35]. But spatial averaging requires a large number of electrodes in the same region, which cause the main drawback of the method for portable equipment. This not only causes a discomfort to the users, as well as an amount of signals to be recorded and treated. Meanwhile, solutions like wearable sensors might be the answer to discomfort, but at time these solutions produces high noise levels due to a bad contact of electrodes at skin surface producing high levels of noise.

To remove muscle noise artifacts in exercise ECG's, Joseph Suresh et al. [36] proposed the SVD (Singular Value Decomposition) method. For a satisfactory performance, SVD filtering do not requires prior information about the onset or offset points of ECG signal, nor knowledge of heartbeat intervals. This is very important since in the presence of a noisy ECG signal it wouldn't be possible to grasp the right position of the wave. SVD method is based on matrix factorization, and the problem of this technique is the matrix dimension and computational calculations before a possible reduction of the matrix. However, the authors of [36] mentioned that with a minimum value of matrix size, the results performance of the MSE (mean square error) are identical to the results of the Wiener filter MSE using a discrete cosine transform.

One promising solution for noise reduction is the use of adaptive filters. There are several advantages for adaptive filtering approaches: adapting filtering do not needs a priori knowledge of the statistical or spectral properties of the signal and noise; constantly adapt the weights of filter for better performance; when applied to a set of samples does not require higher power computation requirements. For some applications, the drawback of adaptive filtering approach is that requires the correlation of noise with signal. For the case of ECG, this is not a problem due to the possibility to obtain this correlation from the electro in the leg. Several authors, e.g.[37, 38, 39], have done their works in this field of signal processing, but mainly with ECG signals from databases as MIT-BIH.

5 Filtering

Filtering is closely related with signal processing discipline, and can be classified into two main categories, analogue signal processing and digital signal processing. Analogue signal processing is for signals that have not been digitized, which involves linear or nonlinear electronic circuits, such as passive or active filters. Digital signal processing is the processing of digitized discrete time sampled signals, where signal treatment is performed by computers or digital circuits, e.g. Digital Signal Processor (DSP) devices, running mathematical algorithms such as FIR or IIR. Additionally, filtering can be classified into linear or nonlinear process. If the filtered output is a linear function of the input observations, the filters is said to be linear, otherwise the filter is considered nonlinear. Moreover, filtering is directly related with spectral analysis, because the goal of filtering is to reshape the signal spectrum. For that reason, filtering techniques and filter types differing in the way that they reshape the signal spectrum.

This chapter will start with a brief presentation of signal processing methods and then the main focus will be the Adaptive Signal processing technique, based on LMS algorithm.

5.1 Signal Processing Methods

Depending on the statistical distribution of signal, digital signal processing algorithms can assume different realisations. If the signal statistical distribution is

unknown, it is used Non-parametric Signal Processing methods. These methods lead with signals in a "blind" way, i.e., they do not care about the signal itself, because they are not specialised to any particular class of signals. The drawback is that they can lose performance due to their generality. Some examples of non-parametric methods include digital filtering and transform-based signal processing methods such as the Fourier analysis and discrete cosine transform. By other hand, if the statistical distribution of signal is known, it is commonly used Model-Based Signal Processing methods. Model-based methods normally outperform non-parametric methods, since they make use of more information in the form of a model of the signal process. These signal processing methods use a description of the expected patterns in the signal process, for these cases the methods are more dedicated and less generalist. However, they can be sensitive to signal deviations due to their restrictions[19, 40]. They are commonly used in low-bit-rate speech coding, digital video codification and speech recognition.

Filtering has a close relationship with signal spectrum, and for that reason, they can be classified in two big groups: FIR filters and IIR filters.

FIR filters are non-recursive filters, because only the input is used in the filter

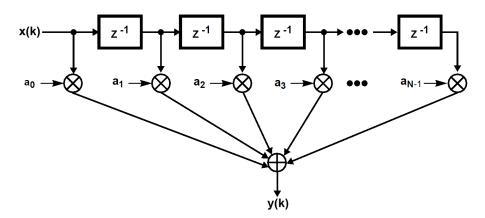


Figure 5.1: FIR Structure

algorithm, Figure 5.1 shows a block diagram of an FIR filter, whit an input x(k) and an output y(k). The output y(k) is defined as:

$$y(k) = a_0 x(k) + a_1 x(k-1) + a_2 x(k-2) + \dots; k = 0, 1, \dots, N-1.$$
 (5.1)

Leading to:

$$y(k) = \sum_{i=0}^{N-1} a_i x(k-i)$$
 (5.2)

Where a_i is the filter feed forward coefficients needed to generate the necessary filtering response, such as low-pass or high-pass, and N is the number of filter taps contained in the function, Z^{-1} is the signal delay and k is the discrete-time index. The a_i coefficients are the zeros of the filter.

This filters have the advantage of always being stable and having linear phase shifts. The downside of FIR filters is that they are less efficient in terms of computer time and memory than IIR filters[20].

FIR filters uses feed-forward calculations only, and in if we allowed feed-back, then the filter impulse response is non-zero over an infinite length of time. This is called IIR filters, which is represented in Figure 5.2.

Figure 5.2 shows a block diagram of an IIR filter, whit an input x(k) and an output

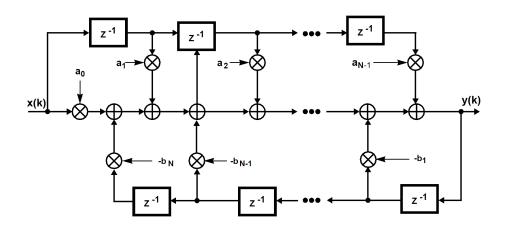


Figure 5.2: IIR Structure

y(k). The output y(k) is defined as:

$$y(k) = a_0 x(k) + a_1 x(k-1) + a_2 x(k-2) + \dots - b_1 y(k-1) - b_2 y(k-2); k = 0, 1, \dots, N-1.$$
(5.3)

Leading to:

$$y(k) = \sum_{i=0}^{N-1} a_i x(k-i) - \sum_{i=1}^{N-1} b_i y(k-i)$$
 (5.4)

Where b_i is the filter feedback coefficients, which is the poles of the filter, and the remaining variables are equal to the FIR filter.

Due to the existence of poles, IIR filters can be unstable, which can be a disadvantage. However, IIR filters are sometimes preferred over FIR filters, because it is possible to achieve the same transition region as FIR filters with less order.

FIR and IIR filters are considered fixed¹; their characteristics are projected to a specific signal, and independently of their dynamics or statistical properties their parameters remains static. To lead with signals whose statistical properties are unknown, fixed algorithms do not process these signals efficiently. Due to this inefficiency, new methods have been studded. This new methods are self-designing systems defined as adaptive filters. Adaptive filters may be classified into supervised adaptive filters, that are based on training sequence that provides different realizations of a desired response for a specified input signal, or unsupervised adaptive filters, which performs the adjustments of their free parameters without requiring a desired response. These filters are commonly used where there is no access to a desired response, e.g. system identification.

5.2 Adaptive Signal Processing

Aiming to achieve best filtering performance, signal processing methods have progressed considerably in algorithm complexity. In general, the computational requirement for signal processing methods have being increased exponentially face to algorithmic complexity. Therefore, finding an algorithm with ability to filtering signals efficiently, with automatic performance adaptation, and at same time offering a good balance between performance and computation requirements, becomes an interesting motivation to work with non-classical filtering² schemes as adaptive signal processing techniques. Conversely to classical FIR and IIR filters, adaptive filters automatically changes theirs characteristics, by optimizing the internal parameters.

It is important to refer the close relationship of the adaptive signal processing technique with Wiener filter. Wiener filter is based on the minimization of the Mean Square Error (MSE) value of signal that is defined as the difference between some desired response and the actual filter output. But, it is only possible to design a Wiener filter with optimal performance if a priori information about the statistics of the data to be processed is known[41]. Adaptive filters are quite similar to Wiener filters, they are based on the same concept, the minimization of the MSE. But unlike Wiener filters, the parameters of adaptive filters are constantly adapted to reach the MSE.

Adaptive filters are widely used in several applications including the treatment of

¹a and b are fixed values.

²An example of classical filters are FIR and IIR

biomedical signals. Biomedical signals such as ECG, EMG, and Electroencephalography (EEG) are important in diagnosis and patient monitoring. But these signals have very small amplitude, therefore they are commonly affected by noise. It is difficult to filter noise from these signals, and errors resulting from filtering may distort them.

5.2.1 Adapting Filtering Scheme

The complete specification of an adaptive system consists in three main points: application, structure and algorithm[42].

Application What is the application where the filter will be used? The type of application is defined by the signals applied to the input and the desired output signals. The number of different applications in which adaptive techniques are being successfully used increases every day. Some examples are echo cancellation, equalization of dispersive channels, system identification, signal enhancement, adaptive beam forming, noise cancelling, and control.

Structure Which filtering structure better satisfy the characteristics of application? Adaptive filters can be implemented in a number of different structures or realizations. The choice of the structure can influence the computational complexity and also the necessary number of iterations to achieve a desired performance level. Basically, the two major classes of adaptive digital filter realizations are the FIR and IIR filters.

Algorithm What kind of algorithm should I use to update the filter parameters? The algorithm is the procedure used to adjust the adaptive filter coefficients in order to achieve the best filtering performance. In such way, adaptation algorithms are based on the mean square error minimization criterion. This error is the difference between the output of the signal processing module and the reference signal. To achieve optimum parameters for the filter, three methods are commonly used: the Recursive Least Square (RLS) method, the LMS and the Stochastic Gradient (SG) method.

5.3 Adapting Filtering Implementation

Adaptive filters are considered nonlinear systems, in the sense that it does not obey the superposition principle. This is a direct consequence of application of

a recursive algorithm whereby the parameters of an adaptive filter are updated between iterations, which turns it data dependent. Their behaviour analysis is more complicated than for fixed filters, because the adaptive filters are self designing filters, from the practical point of view their design can be considered more proactive solution than for the cases of digital filters with fixed coefficients. Adaptive filters are used for non-stationary signals and environments or in applications where a sample-by-sample process adaptation or a low processing delay is required.

Figure 5.3 shows a typical signal denoising setup based on Adaptive Filtering. The primary input is the x(k) with noise $n_1(k)$, and the noise correlated reference input corresponds to noise input signal $n_2(k)$. The $n_2(k)$ needs to be correlated with signal from primary input.

Figure 5.4 shows a N-tap transversal adaptive FIR filter, where the relation between

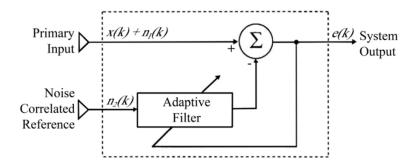


Figure 5.3: Typical signal denoising setup Adp. [1].

filter input x(k) and filter output y(k) is given by:

$$y(k) = \sum_{i=0}^{N-1} W_i(k)X(k-i)$$
 (5.5)

where k is the discrete-time index, N is the number of filter taps contained in the function, Z^{-1} is the signal delay and the parameter vector W_i is the Wiener filter coefficient vector. This equation is identical to Equation (5.2), where the filter coefficients a_i were replaced by the Wiener coefficients.

In Equation (5.5) the filtering operation is expressed in two alternative and equivalent forms of a convolutional sum and an inner vector product.

The Wiener filter error signal, e(k) in Figure 5.4 is defined as the difference between the desired signal d(k) and the filter output signal y(k):

$$e(k) = d(k) - W^{T}(k)X(k) = d(k) - y(k)$$
(5.6)

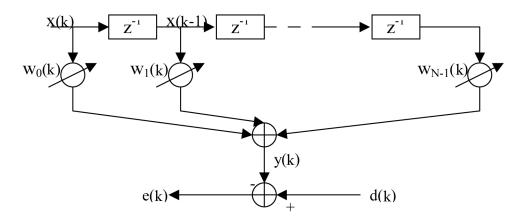


Figure 5.4: N-tap transversal adaptive filter.

Where d(k) is considered the desired signal, it is the primary input in the Figure 5.3, e(k) is the system output and x(k) is the noise correlated reference.

In Equation 5.6, for a given input signal x(k) and a desired signal d(k), the filter error e(k) depends on the filter coefficient vector W. The Equation (5.6) can be expanded for N samples of the signals d(k) and x(k) with P as the filter length:

$$\begin{pmatrix} e(0) \\ e(1) \\ e(2) \\ \vdots \\ e(N-1) \end{pmatrix} = \begin{pmatrix} d(0) \\ d(1) \\ d(2) \\ \vdots \\ d(N-1) \end{pmatrix} -$$

$$-\begin{pmatrix} x_{(0)} & x(-1) & x(-2) & \cdots & x(1-P) \\ x_{(1)} & x(0) & x(-1) & \cdots & x(2-P) \\ x_{(2)} & x(1) & x(0) & \cdots & x(3-P) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{(N-1)} & x(N-2) & x(N-3) & \cdots & x(N-P) \end{pmatrix} \cdot \begin{pmatrix} w_0 \\ w_1 \\ w_2 \\ \vdots \\ w_{P-1} \end{pmatrix}$$
 (5.7)

In a compact vector notation this matrix equation may be written as:

$$E = D - XW (5.8)$$

where E is the error vector, D is the desired signal vector, \underline{X} is the input signal matrix and $\underline{X}W = Y$ is the Wiener filter output signal vector. In Equation (5.7), if the number of signal samples is equal to the number of filter coefficients N = P, then we have a square matrix equation, and there is a unique filter solution W, with

a zero estimation error e = 0, such that $y = \underline{X}W$. If N < P then the number of signal samples N is insufficient to obtain a unique solution for the filter coefficients, in this case there are an infinite number of solutions with zero estimation error, and the matrix equation is said to be underdetermined. In practice, the number of signal samples is much larger than the filter length N > P; in this case, the matrix equation is said to be over-determined and has a unique solution, usually with a non-zero error.

5.3.1 Least Mean Square vs Recursive Least Square

LMS and RLS can be considered a simplest form of the steepest-descent search³. LMS was the first algorithm used to design a linear adaptive filter algorithm by Widrow and Hoff in 1959. The LMS algorithm has established itself as the workhorse of adaptive signal processing for two primary reasons: computational efficiency and robust performance [43]. However, for signals with a large spectral dynamic range, the LMS has a no-smooth and slow rate of convergence. In addition if the signal is also non-stationary. *e.g.* speech and audio signals, then the LMS can be an unsuitable adaptation method. LMS algorithms are known as slowly converging algorithm. The speed of convergence define the number of signal intervals that are necessary to obtaining reliable filter coefficients [42][19].

RLS type algorithms have much better starting convergence properties but are much more complex and for that reason, not so suitable for low computational devices. RLS method, has better convergence rate and less sensitivity to the eigenvalue spread than LMS.

5.3.2 The Least Mean Square Algorithm

To achieve the optimum parameters for the filter, were used the LMS method, due to their simplicity and robustness. The LMS algorithm requires only 2N + 1 multiplications and 2N additions per iteration for a N tap weight vector. Therefore it has a relatively simple structure and the hardware requirements are directly proportional to the number of weights.

The aim of LMS algorithm is to find the optimum weights W in Equation (5.9) in such way that starting from some arbitrary initial point in the weights, progressively moves towards the optimum point. This is grasped trough the evaluation of the gradient of error in the Equation (5.9). The LMS algorithm uses a computationally simpler version of steepest-descent method to calculate the optimum weights, which

³Steepest-descent search is a gradient-based method for searching the least square error.

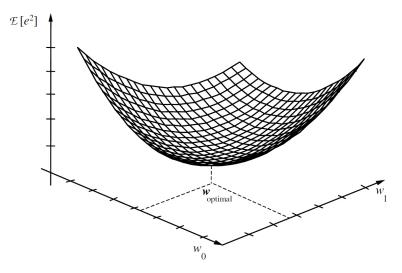


Figure 5.5: MSE surface for a two-tap FIR filter[19].

is the instantaneous squared error defined as:

$$e^{2}(k) = [d(k) - W^{T}(k)X(k)]^{2}$$
(5.9)

For example, for a filter with only two coefficients (w_0, w_1) , the mean square error function is a bowl-shaped surface, with a single minimum point, as illustrated in Figure 5.5. The LMS error point corresponds to the minimum error power. At this optimal operating point the MSE surface has zero gradient.

The LMS adaptation method is defined as:

$$W(k+1) = W(k) + \mu \left(-\frac{\partial e^2(k)}{\partial W(k)} \right)$$
 (5.10)

The instantaneous gradient of the squared error can be re-expressed as:

$$\frac{\partial e^2(k)}{\partial W(k)} = \frac{\partial}{\partial W(k)} [d(k) - W^T(k)X(k)]^2 =$$

$$= -2X(k)[d(k) - W^T(k)X(k)] =$$

$$= -2X(k)e(k).$$
(5.11)

Substituting Equation (5.11) into the recursion update equation of the filter parameters, Equation (5.10) yields the LMS adaptation equation:

$$W(k+1) = W(k) + 2\mu e(k)X(k)$$
(5.12)

where μ is the step-size. This parameter is important, and dictates the speed of error convergence to a minimum.

LMS equation shows that for applications in which the minimum error is non-zero, such as noise reduction, the incremental update term μ would remain non-zero even when the optimal point is reached. Thus at the convergence, the LMS filter will randomly vary about the minimum error point, with the result that minimum error for LMS algorithm will be in excess of this minimum error for Wiener methods[41].

Some of the classical applications of adaptive filtering are system identification, channel equalization, signal denoising, and prediction. Due to the main goal of this work is ECG noise removal, it will only be focusing the signal denoising. The effectiveness of the signal denoising scheme depends on the high correlation between $n_1(k)$ and $n_2(k)$ signals in Figure 5.3. In some applications, it is useful to include a delay of L samples in the reference signal or in the input signal, such that their relative delay yields a maximum cross-correlation between y(k) and $n_1(k)$, reducing the MSE[19]. This delay provides a kind of synchronization between the signals involved.

Practical Results

The aims of this chapter is the application of adaptive filtering technique, based on LMS algoritm, to realise its efficiency when leading with low resolution ECG signals, which is very common in ECG portable devices.

The experiments took place with simulated data against real data, mainly to observe the algorithm efficiency between real noise and simulated noise sources, as well as their performance with a simple ECG signal captured with low cost equipment.

This chapter will start with an exposition of the experience parameters, followed by the tests: EMG denoising with FIR Filter; EMG Denoising with Adaptive Filter and Hum Denoising with Adaptive Filter.

6.1 Experience Parameters

The filtering process was applied to two different ECG signals, one from MIT-BIH data base, and other from a human volunteer through Lead I. Lead I corresponds to one electrode connected to right arm, one to left arm, and a reference electrode connected to right leg. The ECG waveform from MIT-BIH Database has 15 seconds with a sample-rate of 100 Hz. Lead I ECG, was recorded with Biopac System 35 at same sample-rate as MIT-BIH signal, 100 Hz. Both signals were contaminated with noise. MIT-BIH was contaminated with:

• White noise to simulate the muscular electrical activity EMG;

• Sine-wave sweeping between 40.5 Hz and 50.5 Hz to simulate power line noise with a possible frequency oscillation.

White noise was created in Matlab as well as the sine wave sweep. Lead I signal it was contaminated with:

- Real EMG signal;
- Real Power line noise.

EMG signal and power line noise was collected with same equipment as ECG. The EMG was collected with on electrode on right forearm muscle. With an identical process was recorded hum noise, using the body as an "antenna" near to an electromagnetic noise source. It was chosen a source with power line noise and a certain amount of unpredictable noise, for the case, a switch mode power supply.

The parameters for filters are resumed in Table 6.1. The parameters are identical

Noise	Stepsize	Filter	initial Conditions	
			Order	Cut-off frequency
EMG Noise	_	Low-pass FIR	15	0.7
Hum Noise	_	Low-pass FIR	15	0.7
White Noise	0.08	LMS FIR	15	0.4
EMG Noise	0.08	LMS FIR	15	0.4
Sweep Noise	0.2	LMS FIR	11	0.3
Hum Noise	0.001	LMS FIR	11	0.3

Table 6.1: Parameters used for filters

for all the cases from same family (classical FIR and LMS FIR), with an exception for step-size used with real hum noise. For this case, if a bigger step-size is used, the filter never reaches the minimum error. The implementation of the algorithms was done in Matlab.

6.2 FIR Filtering

FIR filtering is used to compare the results of adaptive filtering with a classical filter technique. It was done two experiments, one with EMG noise and other with power line noise.

6.2.1 EMG Denoising with FIR filter

The first experiment carried out was with a FIR filter to remove the real EMG noise from Lead I ECG signal. The parameters for this experience are presented in Table 6.1, and the results of filtering process are shown in Figure 6.1. Figure 6.1a) is the recorded ECG trough Lead I; Figure 6.1b) shows the ECG signal contaminated with real EMG noise; and Figure 6.1c) is the filtered signal. The classical FIR filter cannot remove this EMG noise due to the fact of EMG noise is low frequency random noise which overlaps the ECG signal, and the imposition of fixed weights in the filter.

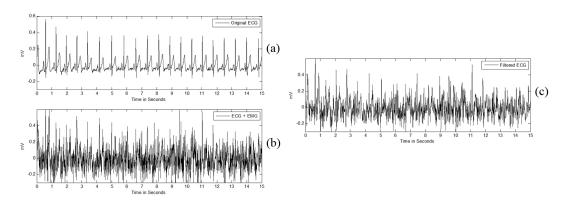


Figure 6.1: Lead I ECG signal contaminated with real EMG noise and filtered with FIR filter. a) Recorded ECG trough Lead I; b) representation of ECG signal contaminated with real EMG noise; c) FIR filtered signal.

6.2.2 Hum Denoising with FIR filter

For the case of real power line noise, the filtering results are shown in Figure 6.2. Figure 6.2a) is the recorded ECG trough Lead I; Figure 6.2b) is the representation of ECG signal contaminated with real hum noise; and Figure 6.2c) shows the result of filtered signal. As expected, a simple low-pass FIR filter can effectively remove this noise, because ECG signal has a frequency spectrum with almost the energy concentrated below 35 Hz, and the hum noise is centred at 50 Hz.

6.3 Adaptive Filtering

Recurring to LMS algorithm to actualise the filter parameters, it was filtered the MIT-BIH and real ECG signal contaminated with EMG and power line noise.

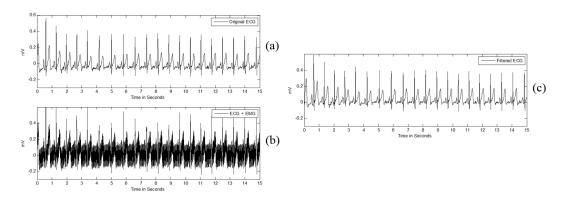


Figure 6.2: Lead I ECG signal contaminated with real power line noise and filtered with FIR filter. a) Recorded ECG trough Lead I; b) representation of ECG signal contaminated with real hum noise; c) FIR filtered signal.

6.3.1 EMG Denoising with Adaptive Filter

The results of MIT-BIH ECG signal contaminated with simulated white noise is shown in Figure 6.3. Figure 6.3a) shows the ECG signal from MIT-BIH database; Figure 6.3b) is a representation of ECG signal contaminated with simulated EMG noise; Figure 6.3c) shows the progress of denoising process; and finally Figure 6.3d) is a representation of the amount of average error during denoising progress.

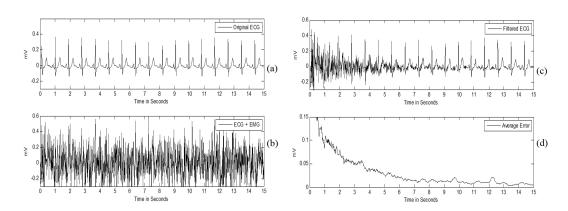


Figure 6.3: MIT-BIH ECG signal contaminated with simulated EMG noise. a) original ECG signal; b) ECG signal contaminated with simulated white noise; c) progress of denoising process; d) average error during denoise progress.

It is possible to see that the process took almost 10 seconds to reach to an acceptable result. Meanwhile, after filtering it is clear the good results of adapting filtering technique, since noise it was practically removed and EGC signal was kept almost unchanged.

It was used the same sequence to filtering the ECG from Lead I. The results of this experiment are shown in Figure 6.4. Figure 6.4a) shows the recorded ECG through Lead I; Figure 6.4b) is a representation of ECG signal contaminated with real EMG noise; Figure 6.4c) shows the denoising process; and Figure 6.4d) is the amount of average error during the denoise progress.

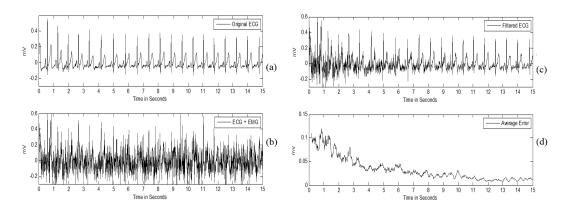


Figure 6.4: Lead I ECG signal contaminated with real EMG noise. a) Recorded ECG trough Lead I; b) representation of ECG signal contaminated with real EMG noise; c) progress of denoising process; d) average error during denoise progress.

Based in same conditions as the ones used in previews case, the filtered signal took slightly more time to rise up identical signal results. This shows that real noise is more difficult to remove, mainly because real EMG has not a so flat distribution as white noise; producing more disturbances into ECG signal.

6.3.2 Hum Denoising with Adaptive Filter

The results of the implementation for remove noise from MIT-BIH ECG signal contaminated with simulated hum noise (a sine wave sweeping between 40.5 Hz and 50.5 Hz) is shown in Figure 6.5. Figure 6.5a) is the original ECG signal; Figure 6.5b) is the ECG signal contaminated with simulated power line noise; Figure 6.5c) it is the progress of denoising process, and Figure 6.5d) it is the average error during denoise progress.

The results of denoising process for this case show that it is possible to reach to a reasonable ECG signal after two seconds. After six seconds, the noise is practically undetectable and the EGC signal still almost unchanged when compared with original.

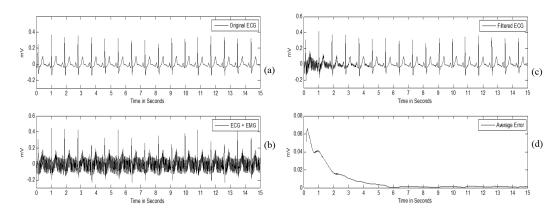


Figure 6.5: MIT-BIH ECG signal contaminated with sine wave sweeping between 40.5Hz and 50.5Hz. a) original ECG signal; b) ECG signal contaminated with simulated hum noise; c) progress of denoising process; d) average error during denoise progress.

Figure 6.6 shows the result of denoising implementation for Lead I ECG signal contaminated with real power line noise. Figure 6.6a) is the original ECG signal; Figure 6.6b) is the ECG signal contaminated with real power line noise; Figure 6.6c) represents the progress of denoising process, and Figure 6.6d) shows the average error during denoise progress.

These results, when compared with results provided before, are slightly worst. It is because real hum noise has more harmonics than simulated noise, mainly due to the exposition to switch mode power supply.

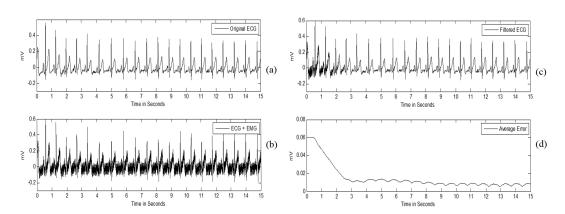


Figure 6.6: ECG signal contaminated with real power line noise. a) original ECG signal; b) ECG signal contaminated with hum noise; c) progress of denoising process; d) average error during denoise progress.

7

Conclusions and Future Work

This chapter will discuss a set of conclusions related to the evaluation and analysis of ECG denoising based on adaptive signal Processing technique. Also, some future work is presented that may enhance and increase the work developed.

7.1 Conclusions

The main purpose of this work was to explore the potentialities of adaptive signal processing in ECG denoising, aiming to prove if adaptive denoising filters are a suitable method for biological signal denoising.

It was used the LMS method to achieve the optimum parameters for the adaptive filter. The LMS adaptive filter showed to be a good choice for ECG noise removal. To verify LMS algorithm performance, it was used two kinds of ECG signals from different sources: One ECG signal is a high resolution record from MIT-BIH, and other is captured from a human volunteer with a low cost electrocardiograph. The noises under consideration were electromyography and power line noises, and it was used simulated and real noise signals. It was evaluated the performance of the algorithm using these signals, where in both cases, it was obtained very good results, proving the high efficiency of LMS adaptive filter compared with FIR filter. The ability of LMS adaptive filter to ECG denoising is very promising even for extreme noisy signals.

It was also shown that Adapting Filter needs a couple of samples, or time, to reach

good results. This could be undesired for some applications, but for EGC monitoring is not crucial since ECG signals are collected during a large period of time giving the possibility to reject the first samples.

It was proven that an adaptive structure is more reliable than fixed algorithms such as classical FIR filter. The denoising results reached from FIR filtering with complex noisy signals, e.g., EMG noise, are very poor proving the inability of this technique to lead with this noise source. For less complex noise signals, e.g., power line noise, where a simple notch filter is suitable, the adaptive filtering does not offer an added value when compared with classical FIR.

7.2 Future Work

The LMS algorithm is not complex and needs low computation requirements, therefore, this method could be useful to run into a portable device based on low cost processors such as microcontrollers for signal processing.

As future work, it will be interesting to implement the LMS adaptive filter in hardware, using a low cost and low power microcontroller with signal processing capabilities.

It will be also important to develop an algorithm to adjust the step-size dynamically, which could be useful to adapt the algorithm to different noise sources.

In this work it was evaluated the performance of LMS adaptive filter to remove electromyography and power line noises from ECG signal. The process was implemented in a sequential mode, i.e., first it was removed electromyography noise and then, with different parameters, it was removed the power line noise. This process could be improved by using a concurrent structure of LMS adaptive filters that is capable of removing the two types of noise in parallel.

Finally, it could be reduced the computational requirements if the process for Wiener tap-weights actualization is done in blocks instead of every sample. The performance will be affected, but depending on the purpose, this could be a profitable solution for very low computational hardware systems.

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