CHAPTER 1

INTRODUCTION

1.1 PRELUDE

The electrocardiogram (ECG) is a non-invasive tool which has been extensively used for diagnosis of heart disease. The ECG is an electrical signal caused by the functioning of the heart. The sum total of millions of cardiac cell depolarization potentials can be represented by an electrocardiogram (ECG). Inspection of the P–QRS–T wave allows for the identification of the cardiac bioelectrical health and disorders of a subject. In order to extract the important features of the ECG signal, the detection of the P wave, QRS complex, and ST segment is essential. Therefore, abnormalities of these ECG parameters are associated with cardiac disorders. Generally, human health state is defined by variety of physiological parameters, which usually are self interdependent. Not all of them are equally informative and important. While designing the overall monitoring system, it is necessary to assess not only importance of measured parameters but also techniques of their measurement and potentiality of implication into practical systems. Medical investigations have proven that the most important parameters are those that specify the work of heart and respiratory system.

VLSI technological advancement has created a major impact on Bio-medical signal processing, with VLSI circuits as reliable devices working at very high speed can be designed which consumes less power in turn increases the life
cycle of the biomedical products (Rabaey 1996). The rapid technological scaling of the MOS devices aids in mapping multiple applications for a specific purpose on a single chip as said by Weste and Harris (2004). In this thesis, adaptive filtering algorithms available in the literature is considered, architectures for VLSI implementation of these algorithms with pipeline and without pipeline is analyzed, suitable modifications of these algorithms are carried out with optimizing area, time and power.

The ECG detection which shows the information of the heart and cardiovascular condition is essential to enhance the patient living quality and appropriate treatment. It is valuable and an important tool in diagnosing the condition of the heart diseases. Each individual heartbeat in the cardiac cycle of the recorded ECG waveform shows the time evolution of the heart’s electrical activity, which is made of distinct electrical depolarization – repolarization patterns of the heart. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of an arrhythmia, which could be detected by analysis of the recorded ECG waveform. Arrhythmia can be classified into following categories: (i) Normal sinus rhythm (NSR). (ii) Pre-ventricular contraction (PVC) or ventricular premature beat (VPB) or extra systole (iii) Ventricular tachycardia (VT) (iv) Ventricular Fibrillation (VF). (v) Supra ventricular tachycardia (SVT) (vi) Atrial premature contraction (APC) etc.

Premature ventricular contraction (PVC) arrhythmia, result from irritated ectopic foci in the ventricular area of the heart. These foci cause premature contractions of the ventricles that are independent of the pace set by the sino atrial node. Many studies have shown that PVCs, when associated with myocardial infarction, can be linked to mortality. So is the case with other arrhythmias. Consequently, their immediate detection and treatment is essential for patients with heart disease, and may be life-threatening and require
immediate therapy. However, automated classification of ECG beats is a challenging problem as the morphological and temporal characteristics of ECG signals show significant variations for different patients and under different temporal and physical conditions Juan Pablo Martinez et al (2004). In the literature, including signal processing techniques such as frequency analysis Chuck Jr and J.O.Wisback (2003), filter banks Saxena, V Kumar et al (2002), statistical Nibhanupadi et al (2004), heuristic approaches Murugappan et al (2011), hidden Markov models, Wiggins et al (2008), support vector machines M.P.S. Chawla (2011), artificial neural networks (ANNs) Choukari et al (2006), and mixture-of-experts method Ranganathan et al (2012). The performance of ECG pattern classification strongly depends on the characterization power of the features extracted from the ECG data and the design of the classifier (classification model or network structure and parameters). Due to its time–frequency localization properties, the wavelet transform is an efficient tool for analyzing non-stationary ECG signals. The wavelet transform can be used to decompose an ECG signal according to scale, thus allowing separation of the relevant ECG waveform morphology descriptors from the noise, interference, baseline drift, and amplitude variation of the original signal.

Several researchers have previously used the wavelet transform coefficients at the appropriate scales as morphological feature vectors rather than the original signal time series and achieved good classification performance, Alice de Jesus kozakevicius et al and Chuck Jr and J.O.Wisback (2003). Accordingly, in the current Work the proposed feature extraction technique employs the suitable wavelet transform in order to effectively extract the morphological and statistical information from ECG data.
1.1.1 ECG signal components and Cardiac Arrhythmia

ECG is a graphical representation of the electrical activity of the heart’s conduction system recorded over a period of time. Under normal conditions, ECG tracings have a very predictable direction, duration, and amplitude. Because of this, the various components of the ECG tracing can be identified, assessed, and interpreted as to normal or abnormal function. The ECG is also used to monitor the heart’s response to the therapeutic interventions. Because the ECG is such a useful tool in the clinical setting, the respiratory care practitioner must have a basic and appropriate understanding of ECG analysis. Comprising a P wave, a QRS complex and a T wave. The normal ECG configurations are composed of waves, complexes, segments, and intervals recorded as voltage (on a vertical axis) against time (on a horizontal axis). A signal waveform begins and ends at the baseline (isoelectric line). When the waveform continues past the baseline, it changes into another waveform. Two or more waveforms together are called a complex. A flat, straight, or isoelectric line (baseline) is called a segment. A waveform, or complex, connected to a segment is called an interval. All ECG tracings above the baseline are described as positive deflections. Waveforms below the baseline are negative deflections.

Lab VIEW with its signal processing capabilities provides a robust and efficient environment for resolving ECG signal processing problems. Lab VIEW uses icons instead of lines of text to create programs. Unlike text based programming language, Lab VIEW uses the data flow programming, where the flow of data determines execution. The proposed algorithm is executed in two stages. Firstly, it preprocesses the signal to remove the noise from the ECG signal. Then it detects P-wave, T-wave, QRS complex and their onsets and
offsets. Lab VIEW and the related toolkits, advanced signal processing toolkit and math script are used to build the graphical programmed for both the stages.

Important signal processing functions include removal or enhancement of signal components. Filters are extensively employed for the same. Specifically they are used in many cutting edge electronic applications within which they form critical elements. Filters could be analog or digital and may possess an Infinite Impulse Response (IIR type) or a Finite Impulse Response (FIR type). Finite Impulse Response (FIR) digital filters have many applications in a wide range of Digital Signal Processing (DSP) algorithms. The lack of feedback in the design makes them more reliable and robust than their IIR counterparts. In practice, Digital Finite Impulse Response (FIR) Filters are implement in Eq. (1.1) where, p is the order of the filter, $h_i$ are the filter coefficients, $x(n)$ and $y(n)$ are the $n^{th}$ input and output signal samples, respectively.

$$y(n) = \sum_{i=1}^{p} (h_i x(n - i)) \quad (1.1)$$

Functional specifications of semiconductor products change frequently in compliance with market requirements and evolving standards. This necessitates a hardware environment that can be programmed adapted to the changing standards quickly and dynamically. Reconfigurable systems (RS) provide a viable solution to this problem. A common means of realizing RS is through the utilization of field programmable gate arrays (FPGAs).

The wavelet transform has recently emerged as a powerful tool for many applications such as data compression, denoising, feature detection, and biomedical signal processing. Over the past 10 years, many researchers have studied wavelet theory and its applications Martinez et al (2004). This work focuses on a wavelet-based signal detection method and its VLSI design. A method for detecting singularity of a signal using dyadic wavelet transform, Choukari et al (2006). This method uses a correlation between local maxima of
high-frequency components obtained by multi-scale dyadic wavelet decomposition of the signal. Using Lipschitz regularity across the scales, they succeeded in detecting some kinds of singularity from the signal. However, their method is time-consuming to detect singularity of the signal.

In the digitizing biomedical signal analysis, the adaptive Noise Cancelling is a technique to remove the unwanted noise affecting the desired signal within an electronic system. The application of adaptive Noise Canceller is increased in modern communication as it has the advantages of easy implementation, low computational complexity and low power application. This technique can also be applied to low voltage application, high frequency signals and low power circuit design. Digital signal processors have a wide variety of applications in the biomedical signal analysis. Now a day, it is becoming increasingly important in our daily life but it imposes the constraints on area, power, low voltage, speed and cost. The most commonly used design tools used for hardware implementation are Application Specific Integrated Circuits (ASIC), Digital Signal Processors (DSP) and FPGAs, Lan (2008).

Among the various filtering method, LMS (Least Mean Square) algorithm is one of the most widely used adaptive filtering algorithms. The significance of LMS algorithm is its simplicity and robustness, good tracking capabilities both in terms of computational load and easiness of implementation. Moreover, it does not require correlation functions, nor does it require matrix inversion. LMS algorithm is a stochastic implementation of the steepest descent algorithm Meng Joo Er et al (2005).
1.1.2 ASIC Development Cycle

ASIC design steps are required to generate GDSII for the proposed architectures. Consider the below mentioned steps in this work Wai-Kai Chen (2006). Appropriate script files are generated to carry out the steps. Figure 1.1 demonstrates the different phases involved in ASIC development cycle. The design phase consists of the following steps has been told in literature Sebastian Smith (2001).

1. Algorithm modeling and simulation using MATLAB.
2. Design modifications of the algorithm and simulation using MATLAB.
3. RTL models for the proposed work are modeled and simulated using Modelsim.
4. Synthesis of the RTL using proper constraints and libraries are carried out using Synopsys DC compiler.
5. Test circuits for the proposed architecture are carried out using DFT compiler from Synopsys.
6. Formal verification for the proposed model is carried out using Synopsys.
7. Timing analysis for the synthesized net list is carried out using Prime Time.
8. Floor planning of the synthesized net list is carried out using Jupiter XT.
9. Placement and Routing of the synthesized net list is carried out using Astro.
10. Physical verification of the net list is carried out using Hercules and to generate GDSII.
1.1.3 Performance Metrics for Efficient ASIC Design

Figure 1.2 shows the ASIC chip with various available resources. Any design is considered to be the best if it meets the following metrics:

1. **Gate count**: The total number of logic gates required to realize the algorithm. According to Mead and Conway (1999) Logic gates such as NAND, NOR and Basic gates are available as standard cells. Collection of standard cells with different properties is called library. These cells
available in the library are used to synthesize the design. In this work TSMC Library is used for synthesizing the design.

Figure 1.2 Complete die with major resources available

2. **Die size**: The total cell area required to accommodate the logic gates and the I/O cells are required for the design. The total space occupied by the logic and the I/O cells with the routing resources define the total cell area expressed in sq mm.

   In this work, die size of 3.1 mm × 3.1 mm and a core size of 1.9 mm × 1.9 mm cell area are required for the design.

3. **Timing**: The maximum operating frequency at which the design can work. The operating frequency depends on the design complexities such as gate count, library files used for the design, number of routing resources and die size. Terminologies like “Slack” are always estimated to
find the operating frequency of the design. Slack is given by the difference between the required time and the available time. Required time represents the specification time. Available time represents the actual time taken by the design to produce the results. It needs to have a required time to be more than the available time. Hence, slack should always be positive Ku and De Micheli (1992).

4. **Power**: The amount of power generated when all the gates available in the logic are switched on then it gives the maximum power. It is due to three aspects in the design: Dynamic power, Static power and Leakage power. Dynamic power is the most dominating in VLSI design as it depends on the input switching frequency. Chinnery et al (2007) proposed low power design techniques like clock gating, power gating and multi Volt cells dynamic power can be minimized. In this work, clock gating concepts are used for minimizing dynamic power (Nazzareno Rossetti 2005).

5. **I/O Pads**: The number of interfaces required for the logic to establish communication with the external world, minimum number is always on advantage. Figure 1.3 shows the top view of an I/O cell.
The next phase involves the implementation of these specifications. In the past, this is achieved by manually drawing the schematics, utilizing the components found in a cell library. This process is time consuming and is impractical, to overcome this problem, Hardware Description Languages (HDL) was developed from Thomas and Moorby (1991). As the name suggests, the functionality of the design is coded using the HDL. There are two main HDL’s in use today, Verilog and VHDL. Both languages perform the same function, each having their own advantages and disadvantages. Verilog HDL is used here for functionality has been adopted in literature (Basker 2004).

The design is coded using the RTL style using Verilog HDL. It can also be partitioned if necessary, into a number of smaller blocks to form a hierarchy, with a top-level block connecting all lower level blocks (David Smith 2000). The next step is to check the functionality of the design by simulating the RTL code. All currently available simulators are capable of simulating the behavior level as
well as RTL level coding styles Jenkins (1994). The purpose of the test bench is to provide necessary stimuli to the design Richard Munden (2004). It is important to note that the coverage of the design is totally dependent on the number of tests performed and the quality of the test bench.

The Synopsys Design Compiler (DC) tool performs the task of reducing the RTL to the gate-level net list. This process is termed as synthesis. Usually, for small blocks of a design, DC’s internal static timing analysis is used for reporting the timing information of the synthesized design Wayne Wolf (1998). DC tries to optimize the design to meet the specified timing constraints. Further steps may be necessary if timing requirements are not met. Most designs today, incorporate design-for-test (DFT) logic to test their functionality; after the chip is fabricated. The concept of formal verification is fairly new to the ASIC design which performs validation of a design using mathematical methods without the need for technological considerations, such as timing and physical effects. They check for logical functions of a design by comparing it against the reference design. The RTL to gate-level verification is used to ascertain that the logic has been synthesized accurately by DC compiler.

The last part involves verifying the gate-level net list. This too is a significant step for the verification process, since; it is mainly used to verify, what has gone into the layout versus what has come out of the layout. What comes out of the layout is obviously the clock tree inserted net list (flat or hierarchical). This means that the original net list that goes into the layout tool is modified. According to Hachtel and Somenzi (1996) the formal technique is used to verify the logic equivalency of the modified net list against the original net list.

The layout tool performs the placement and routing. Optimal placement location, not only speeds up the final routing, but also produces superior results
in terms of timing and reduced congestion. As explained previously, the constraint file is used to perform timing driven placement. The timing driven placement method forces the layout tool to place the cells according to the criticality of the timing between the cells. After, the placement of cells, the clock tree is inserted in the design by the layout tool. The clock tree insertion is optional and depends solely on the design and user’s preference. Users may opt to use more traditional methods of routing the clock network, for example, using fishbone/spine structure for the clocks in order to reduce the total delay and skew of the clock.

The layout tool generally performs routing in two phases: global routing and detailed routing. After placement, the design is globally routed to determine the quality of placement, and to provide estimated delays approximating the real delay values of the post-routed (after detailed routing) design. If the cell placement is not optimal, the global routing will take a longer time to complete, as compared to placing the cells. Bad placement also affects the overall timing of the design. Therefore, to minimize the number of synthesis-layout iterations and to improve placement quality, the timing information is extracted from the layout, after the global routing phase. Although, these delay numbers are not as accurate as the numbers extracted after detailed routing, they do provide a fair idea of the post-routed timing. The estimated delays are back annotated to Primetime for analysis, and only when the timing is considered satisfactory, the remaining process is allowed to proceed.

Detailed routing is the final step that is performed by the layout tool. After detailed route is complete, the real timing delays of the chip are extracted, and plugged into Primetime for analysis. These steps are iterative and depend on the timing margins of the design. If the design fails timing requirements, post-layout optimization is performed on the design before undergoing another iteration of
layout. If the design passes static timing analysis, it is ready to undergo LVS (layout versus schematic) and DRC (Design Rule Checking) before the tape-out Veendrick (2000). It must be noted that all steps discussed above can also be applied for hierarchical place and route. In other words, one can repeat these steps for each sub-block of the design before placing the sub-blocks together in the final layout and routing between the sub-blocks.

The final placed die with I/O cells and logic cells is physically verified using Hercules. The parasitic extracted from the final net list is verified for timing. The GDS II file for the I/O architecture has been generated, the results such as gate count, timing, power and area has been compared and discussed in detail.

1.1.4 Organization of the Thesis

Chapter 1 gives the introduction to the work and examines the traditional ASIC and FPGA design cycle. The conventional adaptive algorithms and the different work carried out in the literature, their features and shortcomings for the adaptive design are analyzed. The ASIC design technique is investigated to demonstrate the possibility of improving the traditional adaptive algorithms using with and without pipelining.

Chapter 2 Describes the ECG signal detection, and statistical feature estimation using lab view.

Chapter 3 Describes the ECG signal feature estimation using various wavelets.

Chapter 4 Describes the design of digital chip for ECG signal feature estimation.

Chapter 5 The goals of this dissertation are re-examined in this Chapter. Further the directions are also discussed in this chapter.
1.2 IDENTIFYING THE HEART PROBLEM

The heart is composed of muscle tissue that contracts and relaxes in a coordinated manner when an electrical stimulus is applied. The heart’s function is to pump blood around the body, through the arterial system to enable the transport of vital nutrients and oxygen. Like all other muscles, the heart receives its oxygen and nutrients from arteries, which are the coronary arteries in this case. A blockage of these vessels often leads to a heart attack (the cessation of the beating of the heart). In fact, coronary heart disease has been shown to be the leading cause of death in developed countries. Myocardial Infarction (MI), heart failure, angina, and sudden death can all occur from the blockages which occur in the coronary arteries. Following an MI, the conventional treatment is to inject a ‘clot-busting’ de-coagulation agent, in order to remove the blockage. However, often the heart has already suffered much damage and muscle-tissue loss, leading to an increased likelihood of re-infarction Malik M et al. Since the cardiovascular system is controlled by the CNS, deterioration in this control mechanism also leads to cardiac-related problems. The rest of this chapter details how the CNS controls cardiac activity and how this is measured to assess the functionality of this control.

1.3 PHYSIOLOGY OF THE HUMAN HEART

The Figure 1.4 shows the Physiology of human heart. The human heart is controlled by a series of electrical discharges from specific localized nodes within the myocardium (cardiac muscle). These discharges propagate through the cardiac muscle and stimulate contractions in a co-ordinate manner in order to pump deoxygenated blood via the lungs (for oxygenation) and back into the vascular system. The physical action of the heart is therefore induced by a local periodic electrical stimulation. As a result of the latter, a change in potential of
the order of 1mV can be measured during the cardiac cycle between two surface electrodes attached to the patient’s upper torso (usually either side of the heart). This signal is known as the electrocardiogram (ECG). In a normal heart, each beat begins with the stimulation of the Sino Atrial (SA) node, high up in the right atrium which causes depolarization of the cardiac muscle in this locality.

![Figure 1.4 Physiology of human heart](image)

This stimulation is both regular and spontaneous and is the source of the primary pacemaker within the heart with an intrinsic frequency of 100 to 120 beats per minute (bpm). Note that the resulting heart rate is often lower than this because of the complex set of chemical exchanges that occur between the initial stimulation and the subsequent depolarization of the surrounding cardiac tissue. The impulse spreads from the SA node to depolarize the atria (the upper two cavities). The electrical signal then reaches the Atrioventricular (AV) node, located in the right atrium. Normally, an impulse can only reach the ventricles via the AV node since the rest of the myocardium is separated from the ventricles by a non-conducting fibrous ring.
Figure 1.5 Source nodes of electrical stimulation within the heart.

The Figure 1.5 shows the source nodes of electrical stimulation within the heart. The AV node is activated it momentarily delays conduction to the rest of the heart and so acts as a safety mechanism by preventing rapid atrial impulses from spreading to the ventricles at the same rate. If the AV node fails to receive impulses it will take over as the cardiac pacemaker (at a much lower frequency of 40 to 60 bpm). The SA node will inhibit this pace making whenever its impulses reach the AV node. Once the impulse has passed the AV node, it enters the bundle of His. This conducting network spreads out into the inter-ventricular septum and divides into left and right bundle branches. As the impulse moves through this region and into the posterior and anterior fascicles it stimulates depolarization of the ventricles. There is a ventricular pacemaker 2 (with a beat frequency of 15 to 40 bpm) which takes over as the main pacemaker if the AV node fails. After the depolarization of the ventricles, a transient period follows where no further ionic current 2. Strictly speaking it is not localized; all the cells have an innate rhythmicity can be flow through the myocardium. This is known as the refractory period and lasts at least 200ms. There is then a recharging
(repolarisation) of the ventricular myocardium to its resting electrical potential and the heart is then ready to repeat the cycle.

![ECG waveform](image)

**Figure 1.6** One second of a typical ECG waveform for one heart beat. The vertical axis represents the mV fluctuations scaled to ± 1 over the whole record. The horizontal (time) axis shows the sample number (with a sampling rate of 256 Hz, there are 256 samples in one second)

### 1.3.1 ECG waveform generation and recording

A typical ECG waveform comprises of an initial P-wave, followed by the main ‘QRS’ complex and then a trailing T-wave (see Figure 1.6). These waves are defined as follows:

- **P-wave** – The low voltage fluctuation caused by the depolarization of the atria prior to contraction. The atria contain very little muscle and thus the voltage change is quite small.

- **QRS complex** – The largest-amplitude portion of the ECG caused by the ventricular depolarization. The time during which ventricular contraction occurs is referred to as the systole. Although atrial depolarization occurs simultaneously, it is not seen due to the low amplitude of the signal generated by this process.

- **T-wave** – Caused by ventricular depolarization.
The time between ventricular contractions, during which ventricular filling occurs, is referred to as the diastole. Although the R-peak is often the largest amplitude component, the morphology of a healthy ECG can vary greatly from patient to patient with the P- or T-waves sometimes dominating or merging with the QRS complex. Swapping the two electrodes over gives an inverted signal with the R-peak being the lowest (or most negative) part of the signal. The time averaged heart rate (HR$_{60}$) is usually calculated by counting the number of beats in a 60 second time period. The instantaneous heart rate, HR$_{i}$, is 60/RR where RR is the time between successive R-peaks (an RR interval). HR$_{60}$ can vary between 30 and 220 beats per minute (bpm) and although the instantaneous heart rate can be as high as 300 bpm, this is not sustainable for more than a few beats without serious problems manifesting themselves.

Maglaveras, N et al (1998) However, since visual inspection is often used to evaluate these features, and this can be done on only a few cycles of the ECG, the recording is short (typically 10 seconds long). Routine analysis of the ECG does not normally involve such a high number of vectors being recorded. Even in an Intensive Therapy Unit (ITU), when data from many lead configurations is available, only one or two leads are routinely monitored. Typically, leads II and V5 are chosen since they offer the most useful information in the context of medical diagnosis. Note that these two lead configurations are the two channels of ECG data in the standard MIT-BIH database.

1.4 FACTORS INFLUENCING HEART RATE AND ITS VARIABILITY

Apart from the autonomic regulation of the heart via the sympathetic and parasympathetic motor neurons, the average heart rate and the variation of the
RR interval (and hence instantaneous heart rate, HR\textsubscript{i}) are controlled by a variety of other factors.

1.4.1 Intra-patient factors

The following is a list of known changes that can occur for most humans from either internal stimuli or exogenous interventions.

![Figure 1.7](image-url) Two minutes of ECGHR\textsubscript{i}, RR interval and respiration (from upper to lower trace respectively) from a healthy subject exhibiting RSA.

Respiratory Sinus Arrhythmia (RSA) – this phenomenon, initially documented by Hales in 1733 Akselrod et al (1981), is the acceleration or HR\textsubscript{i} on inspiration, and its deceleration on expiration. The magnitude of the effect is highly variable (or non-existent in some older or infirm subjects) and tends to be
larger the slower and deeper the breathing is Malik, M. et al, (1996) Figure 1.7 illustrates this phenomenon whereby the QRS complexes are bunched more closely when the respiration trace is moving upwards indicating inspiration. (Here the respiration signal is derived from impedance pneumography; a 22 kHz signal is passed between two ECG electrodes and as air moves in and out of the thorax, the capacitance and hence electrical impedance of the upper body (between these electrodes) changes. The sinusoidal-like variations in electrical impedance at this frequency are therefore representative of the inhalations and exhalations of the subject.) In this case the breathing is deliberately controlled, at about 4 respirations per minute (rpm) initially and then at 7 rpm. Note that the beat-to-beat heart rate changes synchronously with the (noisy) respiration trace.

RSA is mainly mediated through changes in efferent vagal activity and its magnitude is claimed to provide an index of the level of vagal activity to the heart La Rovere M.T et al. RSA is partly influenced by the physical action of the lungs and the cardiac filling volume from the variations in intrathoracic pressure. However, RSA can be observed in the absence of breathing and therefore the mechanism is partly due to a CNS effect Malik M. Furthermore, changes in HR similar to those caused by RSA have also been observed in denervated hearts and this is thought to be related to increase stretching of the sinus node caused by inspiratory increases in venous return Sleight P et al.

- **Cardiac Output (stroke volume × HR)** changes – At rest, changes in HR between about 80 and 150 bpm have little effect on cardiac output because the increase in HR is compensated for by the decrease in stroke volume. Below about 50 bpm stroke volume tends to be fixed and so output falls with HR.
- **Valsalva Manoeuvre** – A respiratory procedure which is thought to provide a rough guide to the integrity of the autonomic neural pathways
involved Malik, M. et al, (1996). The subject takes a deep breath followed by a maximal expiratory effort against a closed glottis. This generates an intra-thoracic pressure of around 100 mmHg which is transmitted to the intra-thoracic and abdominal blood vessels. Initially, pulmonary arterial pressure increases but venous return from outside this region is impaired so the cardiac output falls and BP decreases. The resulting baroreceptor activity causes a rising HR and vascular resistance together with the restoration of mean arterial pressure. On removal of the obstruction, venous return is initially enhanced causing a marked overshoot of BP and baroreflex-mediated bradycardia. Patients suffering from autonomic neuropathy show a sustained fall in pressure during the procedure with little or no compensatory tachycardia or a following BP overshoot and bradycardia.

- Decreases in Venous Return – A decrease in the amount of blood returning to the heart can be caused by haemorrhage and postural stress (causing blood pooling). Cardiac filling pressures are consequently reduced (hypovolemia) and the intra-vascular volume moves towards the peripheral veins. This normally causes a HR increase in the short term. Those physically disconnected from the CNS by a medical procedure.

- The Baroreflex and the vasovagal reaction – The Baroreflex uses arterial and vascular mechanical stretch receptors to adjust the HR if the BP changes. When venous return decreases, BP remains constant or slightly increases while vascular resistance and HR increase. However, despite these increases in vascular resistance and HR this is not enough to compensate for the falling BP from a decreased return in blood volume. Finally if the venous return is too low there may be an abrupt fall in BP
and loss of consciousness accompanied by a decrease in vascular resistance and HR. This is known as the vasovagal reaction.

- **Thermoregulation** – Peripheral and core body temperature are controlled by both internal and external factors. This may affect peripheral resistance, the resistance to blood flow in the peripheral blood vessels.

- **Embolisms** – When a small blood vessel is obstructed by fragments of material carried by the blood flow the result is often a tachycardic response as well as the destruction of the organ (in whole or part) that is supplied by this vessel.

- **Intra-venous (IV) injections** – Stimulatory or inhibitory chemicals can be intra-venously injected to increase or reduce HR.

- **Circadian Rhythms** – These are defined to be variations in biological activity that appear to have a natural cycle of between 23 and 27 hours, but are often locked into the 24-hour day-night cycle (due to light exposure). The most prominent 24-hour physiological variation in humans is that of the fall in blood pressure and HR for a normal subject while asleep (see Figure 1.8). The factors which affect this variation include the health of a patient’s ANS, circulating and local hormones, level of patient awareness and the strength of the heart itself.
Figure 1.8  BP and HR profile in a normal subject over a 24-hour period.
On the horizontal axis, a time of 16 means 4pm and a time of 28
means 4am. Taken from Mathias C.J. et al

1.4.2 Inter-patient factors

Although it is possible to expect certain differences in baseline (resting) HR
and HRV depending on the type of patient, there are multiple factors that
contribute to these differences. It is therefore difficult to categorize or assess
patients without using demographic data. The major factors that lead to inter-
patient differences in HR and HRV (independently of the intra-patient factors
presented above) are:

- Genetics and family history – Although family history can be an important
  risk factor for cardiovascular disease Carney RM et al., relatively little is
  known about the nature of specific genetic risk factors. Research into this
  area is beginning to grow and some researchers Keating M.T. et al are
  attempting to identify and characterize genes responsible for inherited
  disorders in the hope that this information will also provide some insight into
  common forms of cardiovascular disease.
• Age – HRV is lower in the old and very young although this may be masked by the subject’s sex and overall level of fitness Sinnreich R et al (1998).
• Medical condition and level of fitness – High cholesterol levels tend to be associated with lower HRV Sinnreich R et al 91998).

Furthermore, Blood Pressure Variation (BPV) which affects the overall HRV is known to depend on body mass index, mean BP and BRS, which are known to have a significantly lower within patient population variance than inter-group variance.

1.4.3 HR and HRV Correlation

Coumel et al (1995), stress that the strong correlation between HR and HRV should not be interpreted as the fact that HRV is simply a complex way to measure HR. Although they point out that HR is probably the best index of the Sympathovagal balance, they emphasize that a loss of correlation between HRV and other physiological parameters should be looked for as a sign of deterioration in the patient’s state (such as the haemodynamic state if the correlates are HR and HRV). Furthermore, since HRV tends to be a function of the baseline HR they suggest that it could be advantageous to normalize the HRV using the HR but do not suggest a scheme other than the fact that it should not be linear.

1.5 STATISTICAL INDICES

Statistical HRV indices are calculated on a beat-to-beat basis and are based on Euclidean root-mean square (rms) metrics. They are therefore, sensitive to outliers and more suited to hand-edited data (which is usually short term due
to the labour-intensive nature of such work). Time series indices are generally broken down into two broad categories Kleiger R.E. et al (1995):

1. Variables directly derived from the beat-to-beat intervals, such as the mean HR and the standard deviation (SD) for the entire record.
2. Variables based on the differences between adjacent cycles, such as the proportion of differences between adjacent cycles that exceed an arbitrary limit.

The following indices are recommended by the Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology, Malik M et al (1995).

- **SDNN (ms)** – Standard deviation of all NN intervals (also known as SDRR) usually over 24 hours.
- **SDANN (ms)** – Standard deviation of the averages of NN intervals in all 5-minute segments of the entire (24-hour) recording.
- **RMSSD (ms)** – The square root of the mean of the sum of the squares of differences between adjacent NN intervals.
- **SDNN index (ms)** – Mean of the standard deviations of all NN intervals for all 5-minute segments of the entire (24-hour) recording.
- **SDSD (ms)** – Standard deviation of differences between adjacent NN intervals.
- **NN50 (count)** – Number of pairs of adjacent NN intervals differing by more than 50 ms in the entire recording; three variants are possible - counting all such NN intervals pairs, counting only pairs in which the first interval is longer, and counting only pairs in which the second interval is longer.
• pNN50 (%) – Percentage of adjacent NN differing by more than 50 ms over an entire 24-hour ECG recording.

Many variations of these indices have been investigated with varying degrees of success. For instance, Griffin and Moorman et al recently showed that neonatal sepsis is associated with a reduced baseline HR variability coupled with short-lived decelerations of HR and consequently the mean and SD of such distributions are often similar to those calculated from the ECG of normal (healthy) neonates.

1.5.1 Components in the frequency domain

Heart rate changes occur on a wide range of time scales; millisecond sympathetic changes stimulated by exercise cause an immediate increase in HR resulting in a lower long term baseline HR and increased HRV over a period of weeks and months. Similarly, a sudden increase in blood pressure (due to an embolism for example) will lead to a sudden semi-permanent increase in HR. However, over many months the baroreceptors will reset their operating range to cause a drop in baseline HR and BP. In order to better understand the contributing factors to HRV and the time scales over which they affect the heart it is useful to consider the RR time series (or tachogram) in the frequency domain.

1.5.2 Components in the long term

Power spectral analysis was first introduced into HRV analysis by Akselrod et al (1981). Since then many authors have applied a variety of power spectral
estimation techniques. In order to facilitate inter study comparisons, the frequency spectrum of an RR interval tachogram has been split (by definition) into four frequency bands:

- **ULF**  Ultra Low Frequency  0.0001Hz - 0.003Hz
- **VLF**  Very Low Frequency  0.003Hz – 0.04Hz
- **LF**   Low Frequency  0.04Hz – 0.15Hz
- **HF**   High Frequency  0.15Hz—0.4Hz

Figure 1.9  Typical FFT of RR intervals over 24hrs. Taken from Malik et al (1996). Note that the Meyer waves are masked by the power spectral dominance of the VLF and ULF contributions.

Figure 1.9 shows a typical 24-hour PSD with the above bands marked (using logarithmic scales on both axes). Over such a period, frequencies below 0.04 Hz (VLF and ULF) become dominant around 0.1 Hz) being referred to as Meyer waves and the higher frequency component (around 0.25 Hz) being
attributed to respiration effects. Note the spectral peaks at 0.27 Hz (due to RSA; which corresponds to the recorded rate of respiration of 16 breaths per minute) and at 0.1 Hz (the Meyer waves). There is also a significant VLF contribution below 0.04 Hz.

![PSD of RR intervals](image)

Figure 1.1 0 PSD (linear axes) of RR intervals Note the peaks at < 0.04Hz, 0.1 Hz (probably due to BP fluctuations) and one around 0.27 Hz - a modulation of the RR tachogram due to respiration. From observation of Figure it can be seen that the subject was indeed breathing at about 16 breaths per minute, or 0.27 Hz

1.5.3 The LF/HF ratio and Sympathovagal balance

The Figure1.10 shows the PSD of RR intervals, rhythm within the HF band, synchronous with the respiration rate, are due to the intra-thoracic pressure changes and mechanical variations caused by the action of breathing. The manifestation of the respiration rhythms on the RR tachogram is known as Respiratory Sinus Arrhythmia (RSA). This higher frequency peak (above 0.15 Hz) is mediated almost exclusively by fluctuations of the vagal-cardiac nerve activity and is generally accepted as a marker of parasympathetic activity. The 0.1 Hz peak corresponding to the most dominant of the Meyer waves is mostly mediated by fluctuations of sympathetic nerve activity. Although sympathetic
and parasympathetic mechanisms are involved in the LF band, an increase in LF power has always been observed as a consequence of sympathetic activation. An increase in LF power is therefore accepted as a marker of sympathetic activation by many authors Kamath, M.V, et al (1995).

Furthermore, the wealth of clinical studies that have presented evidence for the LF/HF-ratio being an excellent indicator of recovery Malik M, Singh N and even the HF band alone Valkama et al, illustrates that it would be unwise to discount the HF metric completely at this stage.

The majority of the literature in the field of HRV analysis has demonstrated that frequency domain metrics, rather than time series or geometric metrics, are the most useful indices for assessing patient welfare and differentiating between patient groups Malik M et al. This thesis will therefore concentrate on frequency domain metrics. Furthermore, the origin of long term HRV metrics is unclear and estimates of them may be influenced by factors as diverse as local conditions (e.g. temperature) Malik M and quality of sleep Kamath M V et al (1995). However, short term metrics have been shown to be capable of assessing neurological activity Malik M et al and therefore may have a clinical interpretation as well as be more amenable to controlled experimentation. The scope of this thesis is further narrowed to include studies on only the short term (LF and HF) HRV metrics. It has been shown La Rovere M.T. et al (1998) that BRS and HRV may be loosely correlated and that BRS may prove a better indicator for the onset of fatal arrhythmias. In a recent paper Kim et al. used a method they called complex demodulation, separating the signal into a series of band-pass filtered signals of varying length in order to maximize the resolution. They defined BRS to be the instantaneous amplitude of complex-demodulated oscillations in the RR interval divided by the instantaneous amplitude of complex demodulated oscillations in systolic blood
pressure. They claim that this technique was equivalent to power spectral analysis of the RR tachogram.

La Rovere M.T. et al (1998) state the need for care in the use of BRS since it is not static after myocardial infarction and sometimes improves shortly after the event. Furthermore, they pointed out that it also varies with activity and emotional state, although not necessarily in the same manner as HRV varies with these states. Despite such complications they found that the values of BRS studied in the first month after myocardial infarction remain predictive of outcome during the next one to two years.

1.6 THE CONNECTION BETWEEN HR, HRV, BP AND RESPIRATION

There is no simple connection between HR, HRV and BP although some measures of HR and HRV are often (inversely) correlated. That is, stimuli that increase HR often depress the variability of the HR in the short term. Conversely, activities that cause a drop in the average HR can lead to an increase in short term HRV. Although the strength of this correlation can change over time and from individual to individual, it is useful to consider the cardiovascular system from a static perspective in order to gain an insight into the relationship between the cardiovascular parameters. The cardiovascular system is a pressure controlled system and therefore factors that influence changes in BP will also cause fluctuations in HR. In resting humans, beat-to-beat fluctuations in BP and HR are mainly due to respiratory influences and to the slower Meyer waves. Sleight and Casadei et al. emphasizes that there is much evidence to support the idea that beat-to-beat HR variations are a manifestation of a CNS oscillator which becomes entrained to the respiratory rate as a result of afferent input from broncho pulmonary receptors.
It is generally agreed Sleight et al (2000), however, that coupling of HR, respiration and the cardiac cycle (the flow of blood around the body with its consequent pressures) can be broadly explained as follows: inspiration lowers intra-thoracic pressure and enhances filling of the right heart from extra thoracic veins. Right ventricular stroke volume therefore increases and a consequent rise in the effective pressure of the rest of the (lesser) circulation is observed. The rise in effective pressure in the pulmonary veins leads to an increased filling of the left heart and hence to an increased left ventricular stroke volume.

The resistance and hydraulic capacitances of the lesser circulation create a lag between inspiration and right ventricular output increase and between the rise of effective pulmonary venous pressure and left ventricular filling. A consequence of this is that stroke volume modulation will decrease with increasing respiratory rate (for a given respiratory depth). Furthermore, the phase lag of the stroke volume change with respect to the corresponding respiratory oscillation will increase for higher rates. In reality, at moderately rapid respiratory rates, the BP and stroke volume fall throughout most of the inspiration. Therefore the fall in arterial pressure with inspiration is due to the preceding expiration. Furthermore during expiration, the longer pulse (or RR) interval buffers any change in diastolic pressure caused by the resultant increase in stroke volume, so diastolic pressure changes may correlate poorly with reflex changes. This supports the notion that respiration drives BP changes, which in turn drive the RR (HRi) changes. Diastolic BP changes with respiration are quite small since the inspiratory tachycardia tends to reduce any inspiratory fall in diastolic pressure (as there is less time for the diastolic pressure to drop).

This observation was first explained by DeBoer et al (1987) and although there have been other mathematical models proposed since then (such as the
Baselli Model and the Saul Model), most experimental evidence is thought to support DeBoer’s model Sleight et al (2000).

1.6.1 Standard terminology

When using time-domain indices, it was recommended that at least two of the following four measures are used Bracic M et al: SDNN and HRV triangular index for an estimate of overall (long term) HRV, SDANN for an estimate of the long-term components of HRV and RMSSD. The choice should be specific to the type of medical condition being considered and the type of data that it is possible to collect. Furthermore it is inappropriate to compare time domain measures, especially for long term recordings that are derived from ECGs of different time lengths.

For frequency domain measures the Task Force recommended that the number of samples used for the calculation, the size and type of spectral window used and the method of calculating the power in respect of the window is reported to allow inter-study comparisons. Furthermore, when using parametric methods, the type of model, the number of samples, the central frequency for each component and the model order should be quoted. Reporting statistics to test the reliability of the model (such as the prediction error whiteness test for goodness of the fit and the optimal order test to check the suitability of the model order used) is also important.

1.7 STRESS

Stress is a kind of an unbalanced state of human due to either increased physical, mental, emotional, and behavioral demands. Today, the stress is one of the common factors for several medical diseases (Smith 2000). As of
consequences, stress will severely affect the human over day by day activities. Several researchers are working on to identify and measure the stress through different modalities. Indeed, the complex characteristics of human response are one of the major setbacks of this research to become successful. In order to resolve this problem, many research methodologies were developed over the past few decades to compute the stress Seraganian, P. et al (1997). Initially, most of the stress related works are related to biochemical sample analysis (urine, saliva and blood) Tulen, H.M. et al, (1989) and it is intrusive measurement and difficult to acquire the stress states in a simple manner. In addition, offline analysis is only possible in this method and difficult to extend the real time stress level measurement. Secondly, the questionnaire based approach is useful to identify the life time stressful threatening situations and current mental state Holmes, T. et al, (1967). However, these methods are not highly successful due to the 100% based on the response to the responses of questionnaire. Recently, the physiological signals based approach is quite successful to resolve the above issues of two methods and possible to develop the real time stress measurement tool by resolving some burden in this work, considerations in this field. Initially, Tulen, H.M. et al, (1989) started to investigate the stress through physiological signals (ECG, EMG and GSR) by using stroop color word test.

The DWT is used for extracting the HRV features and fuzzy classifier is used to classify their stress levels. In addition to the above signals, some physiological signals such as Blood Volume Pulse (BVP), Pupil Diameter (PD), Skin Temperature (ST) and GSR are also used for identifying the subject stress in stroop colour word test experiments Tulen, H.M et al(1989), Svetlak, M., et al (2010), Pehlivanoglu, B., et al (2005), and A, Lundberg, U et al (2004).

Smith, et al (2000) started that stress is a kind of an unbalanced state of human due to either increased physical, mental, emotional, and behavioral
demands. Today, the stress is one of the common factors for several medical diseases. As of consequences, stress will severely affect the human over day by day activities.

Castro, M.N et al (2008) investigated that Patients with schizophrenia exhibit a normal response to the mental arithmetic stress test as a standard test of autonomic function but in contrast with healthy individuals, they maintain stress-related changes of cardiac autonomic function beyond stimulus cessation.

Tulen, M.N et al (1989), proposed stroop color word test experiments to identify the subject stress level based on some physiological signals such as Blood Volume Pulse (BVP), Pupil Diameter (PD), Skin Temperature (ST) and Galvanic Skin Response (GSR). The Support Vector Machine (SVM), Naive Bayesian, and decision tree classifier were used to classify stress levels of the subjects.

Karthikeyan, et al (2011) recommended that the Heart Rate Variability (HRV) of ECG signal was one of the primary measures to identify the stress levels and it was evidently reviewed and analyzed. Most of the researchers have analyzed the Autonomic Nervous System (ANS) activity of the subject from ECG signals for analyzing the impact of stress on the subjects. In general, ANS activity is categorized into parasympathetic and sympathetic activities.

In J .Taelman, et al (2008) the stress related HRV signal were derived from RR Interva variance of ECG signal over three frequency bands such as High Frequency (HF) (0.15 Hz- 0.5 Hz), Low Frequency (LF) (0 Hz -0.08 Hz), and Middle Frequency (MF) (0.08 Hz-0.15Hz). The HF has mostly dominated in the parasympathetic activity, and the LF is dominating in both the sympathetic and parasympathetic activities. However, MF does not reflect any of the ANS activities and it is considered for estimating the human stress levels in But, MF is only carried out only few studies P. Rani, et al, (2002) suggested to extract the
statistical features from LF and HF frequency bands for nonlinear signal analysis in time domain methods such as Auto Regressive, Auto Regressive Moving Average (ARMA), Short Time Fourier transform (STFT) and frequency domain methods such as Fast Fourier Transform (FFT), Smoothed Pseudo Wigner-Ville Distribution (SPWVD) and time-frequency domains such as DWT and Empirical Mode Decomposition (EMD). In recent years, DWT has become a highly successful in the nonlinear signal analysis due to its exceptional time-frequency domain information retrieval from the non-linear signals. However, the selection of appropriate mother wavelet function is getting major attention on deriving the best performance in feature extraction. The stroop color word test was used as stress inducement stimuli to induce evoke the stress and ECG signals were simultaneously acquired. Infinite Impulse Response (IIR) 4th order elliptic band Pass filter and notch filter are used to remove the effects of noises from the acquired ECG signals. ECG and derived ECG signal from HRV and is mainly considered in this work. The HRV signals are derived from the ECG signal using a Pan Tompkins algorithm. The standard time domain statistical features are analyzed in order to validate the stress samples. Significantly in this work, low frequency bands (0.04-0.5) of ECG signal are directly extracted instead of analyzing HF and LF band of HRV. In this work limited duration of ECG signal is acquired through our protocol (less than 1 minute) and normally stimulated laboratory stress induction is moreover acute nature. E.g., the stroop color word test, cold presser test and mental arithmetic are conducted very limited duration time.

1.8 SURVEY OF WAVELETS

The wavelet transform has emerged over recent years as a powerful time–frequency analysis and signal coding tool favored for the interrogation of
complex non-stationary signals. Its application to bio signal processing has been at the forefront of these developments where it has been found particularly useful in the study of these, often problematic, signals: none more so than the ECG. In this review, the merging role of the wavelet transform in the interrogation of the ECG is discussed in detail, where both the continuous and the discrete transform are considered in turn.

This limitation can be partly overcome by introducing a sliding time window of fixed length to localize the analysis in time. This local or short time Fourier transform (STFT) provides a degree of temporal resolution by highlighting changes in spectral response with respect to time. A number of alternative time–frequency methods are now available for signal analysis. Of these, the wavelet transform has emerged over recent years as the most favored tool by researchers for analyzing problematic signals across a wide variety of areas in science, engineering and medicine (Addison 2002). It is especially valuable because of its ability to elucidate simultaneously local spectral and temporal information from a signal in a more flexible way than the STFT by employing a window of variable width. Thus wavelet transforms produce a time–frequency decomposition of the signal which separates individual signal components more effectively than the traditional short time Fourier transforms (STFT). This flexible temporal–spectral aspect of the transform allows a local scale-dependent spectral analysis of individual signal features. In this way both short duration, high frequency and longer duration, lower frequency information can be captured simultaneously. Hence the method is particularly useful for the analysis of transients, aperiodicity and other non-stationary signal features where, through the interrogation of the transform, subtle changes in signal morphology may be highlighted over the scales of interest. Another key advantage of wavelet techniques is the variety of wavelet functions available,
thus allowing the most appropriate to be chosen for the signal under investigation. This is in contrast to Fourier analysis which is restricted to one feature morphology: the sinusoid. In its discrete form using orthogonal wavelet bases, the wavelet transform is particularly useful in signal coding, allowing information within the signal to be localized within a number of pertinent coefficients for compression purposes. Wavelet transform analysis has now been applied to a wide variety of biomedical signals including: the EMG, EEG, clinical sounds, respiratory patterns, blood pressure trends and DNA sequences Dupuis and Eugene (2000), Hadjileontiadis and Panas (1997), Marrone et al (1999), Khalil and Duchene (2000), Petrosian et al (2000), Arneodo et al (1998) and the subject of this review, the ECG. This review will examine the emerging role of wavelet transform analysis in the study of the ECG, ECG timing, morphology, distortions and noise.

Producing an algorithm for the detection of the P wave, QRS complex and T wave in an ECG is a difficult problem due to the time varying morphology of the signal subject to physiological conditions and the presence of noise. Recently, a number of wavelet-based techniques have been proposed to detect these features. Senhaji et al (1995) compared the ability of three different wavelets transforms (Daubechies, spline and Morlet) to recognize and describe isolated cardiac beats. Sahambi et al (1997) employed a first-order derivative of the Gaussian function as the wavelet for the characterization of ECG waveforms. They then used modulus maxima-based wavelet analysis employing the dyadic wavelet transform to detect and measure various parts of the signal, specifically the location of the onset and offset of the QRS complex and P and T waves. Sahambi et al showed that the algorithm performed well in the presence of modeled baseline drift and high frequency noise added to the signal. They used
the method to determine timing intervals of the ECG signal including the widths of the QRS complex, T and P waves, and PR, ST and QT intervals.

To extract the frequency band information of ECG, the DWT has been widely used. The proper wavelet function plays important role for feature extraction of biomedical signals. (E.S.E. Dahshan 2010) extracted the frequency band information of ECG using DWT. The choice of proper wavelet function plays important role for feature extraction. Three wavelet functions namely: “db4”, “coif5” and “sym7” were considered due to its significant performance in ECG signal denoising. Eight statistical features (mean, standard deviation, power, energy, entropy, covariance, maximum and minimum of wavelet coefficient’s) were extracted using above wavelet functions from two frequency bands (HF (0.14 Hz -0.5 Hz) and LF (0.05 Hz -0.14 Hz) and three frequency bands ratio (LF/HF, LF/ (LF+HF) and LF/ (LF+HF)). Finally, the computed features of ECG were normalized and classified into two states namely stress and relaxed using non-linear classifier (KNN).

Metin Akay, et al, (1995) studied that the wavelet transform (WT) as a method for characterizing the maturational changes in electro cortical activity in 24 fetal lambs ranging from 110–144 days gestation (term 145 days). The WT, based on multi resolution signal decomposition, is free of assumptions regarding the characteristics of the signal. The approximation of the electro cortical activity at resolutions varying from 2 j+1 to 2 j can be extracted by decomposing the signal on a wavelet orthonormal basis of L 2(R). They have performed multi resolution decomposition for four sets of parameters D 2j, where -1 < j < -4. The four series WT represented the detail signal bandwidths: (1) 16–32 Hz, (2) 8–16 Hz, (3) 4–8 Hz, (4) 2–4 Hz. The data were divided into three groups according to gestational age: 110–122 days (early), 123–135 days (middle), and 136–144 days (late). In the early group, the power was highest in the fourth signal bandwidth,
with relatively low power in the other bands. Increase in gestational age was characterized by increased power in all four bandwidths. Comparison of the cumulative distribution function of the power in the four wavelet bands confirmed the presence of two statistically different patterns in all three age groups. These two patterns correspond to the visually identified patterns of HVSA (high-voltage slow activity) and LVFA (low-voltage fast activity). The earliest development change occurred in HVSA, with progressive increase in power in the 2–8 Hz band. Later changes occurred in LVFA, with a significant increase in power in the 16–32 Hz band. The same database was also analyzed by the short-term Fourier transform (STFT) method, the most common time-frequency analysis method. Comparison of the results clearly showed that the WT provided much better time-frequency resolution than the STFT method and was superior in demonstrating maturational changes in electro cortical activity.

The intelligent virtual ECG device by integrating dyadic wavelet algorithm for QRS detection, recording and identification with the facilities of the detection of heart rhythm and offline analysis of prerecorded ECG signal has been proposed. Besides all these development in biomedical engineering, the designed system in paper facilitates the automatic removal of noises and filtration of acquired signal on virtual cardiographs and this system can be used for analysis, identification of peak QRS and auto diagnose. The work reported by Lok-Kee Ting and Roger Woods (2005) discusses FPGA Implementation of a Pipelined Adaptive LMS Predictor for Electronic Support Measures Receivers. The architecture considers the Delayed LMS (DLMS) algorithm for which Direct Form (DF) and the Transposed Form (TF) structures are considered and implemented on fine-grained FPGA. With parallelism being supported on FPGA it becomes very simple to implement the design using software tools on FPGA. However, ASIC implementation details have not been considered.
Ahmed Elhossini et al (2004) reports implementation of a LMS Adaptive Filter for Audio Processing on FPGA. The different architectures were proposed namely software, software/hardware and hardware for implementing a Least Mean Square (LMS) adaptive filtering algorithm using a 16 bit fixed-point arithmetic representation. The on-board AC97 audio codec is used for audio capture/playback, and the Virtex-II FPGA chip is used to implement the three systems. A comparison is then made between the three alternative architectures with different filter lengths for performance and area. However this work consumes more area and affects the speed of the system because of software implementation.

Shou-Sheu Lin and Wen-Rong Wu (1996) present ASIC design of an LMS-based Decision Feedback Equalizer for TDMA Digital Cellular radio. An adaptive decision feedback equalizer (DFE) is the common device to compensate the inter symbol interference caused by the multi-path effect. DFEs use the recursive least square (RLS) algorithm. However, it is known that the RLS algorithm is computationally intensive and not easy to implement. The LMS is well known for its simple structure. In this paper, they have considered the ASIC design of the LMS DFE. They designed LMS architecture, which occupies less area. However the design consumes more power, as power optimization leads to increase in device sizes.

Lakshmanan et al (2002) presents FPGA implementation of a simple and novel technique for RLS ADF's based Adaptive Filter Algorithm. Trade off between quality and cost of implementation is highlighted in this work. Subsystems like Main-Controller units, Sub-control Unit, MAC, RLS Divider Unit and RAM unit are developed efficiently. The Main-Controller and the Sub-control Unit forms the main core of the RLS architecture. The main controller controls the RLS operation and keeps track of the states; the Sub-control Unit
executes each process within the State. The mean square error between the desired signal and the filtered signal becomes very small at about 120 iterations and at about 300 iterations the error will be almost zero. The maximum operating frequency is 30MHz.

Marque et al (2005) Journal of Electromyography and Kinesiology presented a paper on Adaptive filtering for ECG rejection from surface EMG recordings. They said surface Electromyograms (EMG) of back muscles are often corrupted by electrocardiogram (ECG) signals. This noise in the EMG signals does not allow appreciating correctly the spectral content of the EMG signals. Several methods have been proposed to reject the ECG noise from EMG recordings, but seldom taking into account the eventual changes in ECG characteristics during the experiment. They propose an adaptive filtering algorithm specifically developed for the rejection of the electrocardiogram corrupting surface Electromyograms. The best results were obtained with the simplified formulation of a RLS algorithm.

Greenberg (1998) presented a “Modified LMS Algorithms for Speech Processing with an Adaptive Noise Canceller”. The modified LMS algorithms are particularly suited for single (such as Speech) that exhibit large fluctuations in short-time power levels.

Nishikawa and Kiya (2000) proposed a fast implementation technique for RLS adaptive filters. The technique has an adjustable parameter to trade the throughput and the rate of convergence of the filter according to the applications. The conventional methods for improving the throughput do not have this kind of adjustability so that the proposed technique will expand the area of applications for the RLS algorithm. The improvement of the throughput can easily be achieved by rearranging the formula of the RLS algorithm and therefore there is no need for faster processing elements (PE) for the improvement.


Widrow et al (1976) has described the performance characteristics of the LMS adaptive filter by deriving relationship between speed of adaptation and performance of adaptive system in both stationary and non-stationary conditions.

developed an improved version of the stochastic gradient LMS algorithm as frequency domain LMS algorithm for predictor adaptation in ADPCM speech compression systems.


1.8.1 Discussion and concluding remarks

The wavelet transform has emerged over recent years as a key time–frequency analysis and coding tool for the ECG. As we have seen in this review, its ability to separate out pertinent signal components has led to a number of wavelet-based techniques which supersede those based on traditional Fourier methods. In its continuous form, the CWT allows a powerful analysis of non-stationary signals, making it ideally suited for the high-resolution interrogation of the ECG over a wide range of applications. In its discrete form, the DWT and its offshoots, the SWT and WPT, provide the basis of powerful methodologies for partitioning pertinent signal components which serve as a basis for potent compression strategies. It is interesting to note that researchers coming to the wavelet transform tend to take an either/or approach to their study: either concentrating on the DWT or the CWT relatively few explore both in depth. The DWT has interesting mathematics and fits in with standard signal filtering and encoding methodologies. It produces few coefficients, its practical application is simple with many off-the-shelf software toolboxes available (e.g. Mat lab
Wavelet Tool box), and the user does not have to worry about losing energy during the transform process or its inverse. However, it exhibits non-stationary and coarse time–frequency resolution. The CWT, on the other hand, allows arbitrarily high resolution of the signal in the time frequency plane, which is a necessity for the accurate identification and partitioning of pertinent components. However, the discretization of the continuous wavelet transform, required for its practical implementation with discrete signals, involves a discrete approximation of the transform integral (i.e. a summation) computed on a discrete (but not dyadic) grid of a scales and b locations. The inverse continuous wavelet transform is also computed as a discrete approximation. How close an approximation to the original signal is recovered depends mainly on the resolution of the discretization used and, with care, usually a very good approximation can be recovered. CWT algorithms are widely available, however, the inverse C This either/or approach, evident in the literature, has led to a number of papers appearing where the discrete transform has been used in the analysis of the signal, whereby the coarseness of the resulting decomposition makes identification of pertinent features within the transform difficult, if not practically impossible. The non-stationary of the DWT can also cause problems in terms of repeatability and robustness of the analysis, unless it particularly lends itself to an ensemble averaged method. Although the stationary wavelet transform can overcome this, it is still limited to dyadic frequency scales and involves significantly more coefficients than the DWT. The author expects that the future will see the application of the CWT to many of the problems that the DWT (or SWT) has previously been applied to. The often cited argument for using the DWT in an analysis role, because the CWT is significantly more expensive computationally, is most often a spurious one: especially true given the computing power now generally available even in fairly basic medical
devices. It is also envisaged that further study of techniques for compacting the information contained in the CWT into a tiny subset of coefficients, such as modulus maxima, ridge following and perhaps even reassignment methods Clifton et al (2003), will lead to further novel CWT-based analysis and compression techniques in the future. It is envisaged that the future will see further application of the wavelet transform to the ECG as the emerging technologies based on them are honed for practical purpose.

1.9 REVIEW OF VLSI

This chapter reviews the previously published literatures, which lays the foundation and basis for further work in this research. This helps to give a better understanding on the topic and also acts as a guideline for this thesis.

The work reported by Lok-Kee Ting and Roger Woods (2005) discusses FPGA Implementation of a Pipelined Adaptive LMS Predictor for Electronic Support Measures Receivers. The architecture considers the Delayed LMS (DLMS) algorithm for which Direct Form (DF) and the Transposed Form (TF) structures are considered and implemented on fine-grained FPGA. With parallelism being supported on FPGA it becomes very simple to implement the design using software tools on FPGA. However, ASIC implementation details have not been considered.

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recordings. They said surface electromyograms (EMG) of back muscles are often corrupted by electrocardiogram (ECG) signals. This noise in the EMG signals does not allow appreciating correctly the spectral content of the EMG signals. Several methods have been proposed to reject the ECG noise from EMG recordings, but seldom taking into account the eventual changes in ECG characteristics during the experiment. They propose an adaptive filtering algorithm specifically developed for the rejection of the electrocardiogram corrupting surface electromyograms. The best results were obtained with the simplified formulation of a RLS algorithm.

Sinead Mullins and Connor Heneghan (2002) presented “Alternative Least Mean Square Adaptive Filter Architectures for Implementation on Field Programmable Gate Arrays”. In this they proposed both the transposed and hybrid forms, which are derived from the delayed LMS, allow for higher speeds without significant increases in power or area. For FPGA implementation, the transposed form is optimal, as power and area are not significantly greater than values found for the direct form, despite the higher maximum frequency. Even at greater number of taps, the maximum frequency of the transposed form is not degraded, despite the input data bus driving an increased number of multipliers.

Greenberg (1998) presented a “Modified LMS Algorithms for Speech Processing with an Adaptive Noise Canceller”. The modified LMS algorithms are particularly suited for single (such as Speech) that exhibit large fluctuations in short-time power levels.

algorithms with improved convergence performance which is used to remove the delays of secondary paths within the coefficient updates.

Nishikawa and Kiya (2000) proposed a fast implementation technique for RLS adaptive filters. The technique has an adjustable parameter to trade the throughput and the rate of convergence of the filter according to the applications. The conventional methods for improving the throughput do not have this kind of adjustability so that the proposed technique will expand the area of applications for the RLS algorithm. The improvement of the throughput can easily be achieved by rearranging the formula of the RLS algorithm and therefore there is no need for faster processing elements (PE) for the improvement.


Widrow et al (1976) has described the performance characteristics of the LMS adaptive filter by deriving relationship between speed of adaptation and performance of adaptive system in both stationary and non-stationary conditions. Georgios and Steven (1997) developed Blind Fractionally Spaced Equalization of Noisy FIR Channels using Direct and Adaptive Solutions. Lan-Da Van and Chih-Hong Chang (2002) developed a new Relaxed Given Rotations (RGR)-RLS algorithm and the corresponding RGR-RLS systolic array which have the same convergence as QRD-RLS.


Miyagi and Sakai (2001) compared the Filtered error LMS with Filtered XLMS algorithm for the variations of error signal, step size and stability conditions. Sumit Roy and Shynk (1990) analyzed convergence properties for nonlinear system using momentum LMS algorithm to train a single layer
Perceptron. Wang and Wang (1995) derived a new delayed LMS algorithm which is a realization of orthogonality principle by minimizing the posteriori squared error.

1.9.1 Summary of the Literature Review

The following are the gaps identified in the literature review carried out till date:

1. In conclusion, it has been shown that the wavelet transform is a flexible time–frequency decomposition tool which can form the basis of useful signal analysis and coding strategies.

2. The convergence of the LMS algorithm is also very sensitive to the Eigen value spread of the correlation matrix of the input data.

3. The convergence of the RLS algorithm is an order of magnitude faster than the LMS algorithm, but its computational complexity is an order of magnitude higher than LMS. The high computational requirement has limited the application of the adaptive algorithms in the past. However, with rapid advances in VLSI technology, now it will be possible to implement complex circuits on a single chip.

4. The existing architectures as reported in the literature review are realized on FPGA, which supports parallelism and pipelining. Hence, the design is reconfigurable, but it does not meet the desired speed, power and area requirements. ASIC implementation of the available architectures with existing standard cells with industry standard tools can provide reliable results and achieve required specifications.

5. The architectures reported adopt the pipelining and parallel processing to an extent to improve the performance; this is restricted by the hardware
resource availability on FPGA. Hence, there is a need for VLSI architectures to be designed and developed adopting pipelining and parallel processing for implementation of adaptive filtering.

6. VLSI architectures for pipeline and without pipeline architectures for FXLMS, ALMS, and NLMS are not reported in the literature. Hence, there is a scope for research in developing and proposing new architectures for adaptive filtering.

7. ASIC implementation of the proposed new architectures for LMS, ALMS, NLMS and RLS with and without pipelining gives scope for research in finding out the performances of the hardware with respect to speed, power and area complexities which results in a new approach in realizing adaptive filtering on ASIC.

1.10 PROBLEM DEFINITION

1.10.1 Problem Definition

The literature survey reveals that adaptive processing systems are implemented on FPGA, due to FPGA supports programmability, pipelining and parallel processing. ASIC design of adaptive algorithms reported in the literature have not attempted to incorporate or exploit pipelining and parallel processing for implementation of LMS and RLS algorithms. This research work considers these algorithms in view of biomedical industry and other applications. The research focuses on developing architectures with and without pipelining for adaptive signal processing for its ASIC implementation.
The objective of this work is to design and implement dedicated chip of adaptive noise canceller algorithms for noise reduction using with and without pipelined architecture to serve the ECG signal processing for stress analysis which is optimized for better area, power and timing.

1.10.2 Research Objective

1. To review literature on to propose new ECG signal processing techniques for stress analysis.
2. To design, develop and acquire the ECG signal, classify the statistical parameter of ECG signal under different population
3. To makes the analysis of heart rate variability using windowing techniques and wavelet transform
4. To propose new architecture for adaptive ECG signal processing with and without pipelining concepts for ASIC implementation
5. To design, develop and verify the proposed architectures to meet the design requirements
6. To compare the different ECG signal classification techniques
7. To draw suitable recommendations based on the results obtained and the work carried out

1.10.3 Plan of Work

2. Understanding ECG signal classification algorithms and architectures.
3. Finding suitable ECG classification techniques for Stress analysis and VLSI implementation for the identified specifications and proposing new architectures for ECG signal processing.
4. Mat lab simulations of the top-level model of the proposed architecture and validation of the same with standard set of results.

5. Developing HDL coding of adaptive noise interference canceller.

6. Functionality verification of the models using test benches.

7. Synthesizing the code and optimization of code for area, power and time.

From the literature review, it has been observed that there exists a need for new architectures incorporating pipelining concepts for implementing adaptive filter techniques using VLSI technology. The best algorithms represented in the literature have been considered with modification by incorporating with and without pipelined concepts. The VLSI implementation of the architecture has been carried out using synopsis.

The RTL to GDS II tool flow is carried out using 130nm micron technology with TSMC standard cell technology. The RTL code for the architecture is modeled using Verilog HDL Mark Gordon Arnold (1999). The functional verification of the algorithm has been verified using Modelsim. Appropriate test vectors have been identified and used to verify the functionality of the design which covers 70% of entire functionality. The RTL code has been synthesized using synoptic design compiler by setting proper constraint such as timing, area and power as adopted in literature Himanshu Bhatnagar (2002). The results obtained are verified with theoretical results. The net list generated is verified for timing using primetime from Synopsis. The net list has been taken through physical design flow; the design has been inserted with the IO blocks and power routings. The design has been taken through floor planning, placement and routing stages. The final placed die with I/O cells and logic cells is physically verified using Hercules as told in Pucknell (1997). The parasitic extracted from the final net list is verified for timing. The GDS II File for the IO
architecture has been generated, the results such as gate count, timing, power and area has been compare and discussed in detail.

1.11 SUMMARY

This chapter highlights the main problems that remain in HRV analysis. In a large proportion of the literature concerning HRV metrics, the data is pre-processed by hand, with experts performing artifact rejection and noise removal. Furthermore, many publications are contradictory in asserting which HRV methods produce useful results. Malik suggests that the perceived need for visual verification and manual correction of long term records has discouraged the assessment of HRV in routine clinical practice and has confined HRV investigations to academic research.

Discusses the ASIC design cycle adopted for analyzing the hardware implementation of the proposed adaptive signal algorithms. The performance matrix for the ASIC implementation as suitable to the proposed work is discussed and identified. The literature review critically identifies the gaps in the existing literature. Based on this gaps identified in the literature, the problem definition for the proposed work is discussed. This chapter also discusses the problem objective, plan of work and the methodology adopted to meet the objective.