SIMULATION OF PHYSIOLOGICAL SIGNALS USING WAVELETS

A Thesis

Presented to

The Graduate Faculty of the University of Akron

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

Soniya Naresh Bhojwani

December, 2007
SIMULATION OF PHYSIOLOGICAL SIGNALS USING WAVELETS

Soniya Naresh Bhojwani

Thesis

Approved: 

Advisor
Dr. Bruce C. Taylor

Department Chair
Dr. Daniel B. Sheffer

Committee Member
Dr. Daniel B. Sheffer

Dean of the College
Dr. George K. Haritos

Committee Member
Dr. Dale H. Mugler

Dean of the Graduate School
Dr. George R. Newkome

Date

ii
ABSTRACT

Increased attention to patient safety, demands for innovation in medical education, and accelerating advances in diagnostic and therapeutic procedures have all promoted a growing interest in the use of simulators for medical training and assessment. The current study proposed and developed a method for approximating and reproducing physiological signals in a programmable simulator using wavelet filtering. This method employed the technique of designing a template from an already existing source data, which then forms the basis of this realistic artificial biomedical signal generator/simulator. The simulated physiological signals included an electrocardiogram, blood pressure, respiratory signal, time derivative of thoracic impedance (dZ/dt), and photoplethysmogram. Templates were also designed for conditions exhibiting premature ventricular contraction, ventricular flutter and left bundle branch block in an electrocardiogram. The software was designed in MATLAB®, and DATAQ® Instruments DI-720 data acquisition system was used to display the simulated output. Evaluation of this simulator model was done both in quantitative and qualitative terms. The results proved that using wavelets for reconstruction of physiological signals minimized distortion and retained the significant features in each signal that was simulated.
ACKNOWLEDGEMENT

“The roots of education are bitter, but the fruit is sweet.”

~Aristotle

The above quote is quite pertinent in my case. The beginning of this research was nonetheless an arduous task at hand, but now that it has reached the completion stage, the fruit no doubt tastes sweet! I would like to begin giving thanks and recognition to the many individuals who have provided both the opportunity and support essential for the completion of this research endeavor. First, I want to thank my advisor, Dr. Bruce Taylor for his guidance and encouragement during the duration of this work. I am honored to have been associated with him. I would also like to extend my thanks to my committee members, Dr. Daniel Sheffer, who is not only a master in statistics but is also a great teacher, and Dr. Dale Mugler for teaching me about wavelets, which forms an essential part of this thesis.

I’m grateful to my all my friends whose encouragements made this thesis a reality. My special thanks to Viraj, whose friendship and strength made life much easier. His support and patience allowed me to think with a clear mind (I finally did it!). My regards and best wishes to the faculty, staff and the students of the Department of Biomedical Engineering and the other departments at University of Akron for their support and help.
in numerous ways. Mr. Rick Nemer and Ms. Bonnie Hinds deserve a special mention here for their assistance and cooperation whenever I needed it. I would also like to acknowledge my fellow lab mates, especially Lily, Nemath and Dyuti for their help and invaluable suggestions all through the progress of my research. Lastly, I would like to thank my family for their love and faith. I owe them more than words can say.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>LIST OF TABLES</th>
<th>viii</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIST OF FIGURES</td>
<td>ix</td>
</tr>
</tbody>
</table>

## CHAPTER

### I  INTRODUCTION

1.1 Objective of the study .................................................................4

1.2 Research Hypothesis ........................................................................5

### II  BACKGROUND

2.1 Electrocardiogram (ECG) .................................................................6

2.2 Blood Pressure ................................................................................8

2.3 Respiratory Signal ............................................................................9

2.4 Photoplethysmogram (PPG) .............................................................10

2.5 Impedance Cardiography and dZ/dt ................................................12

2.6 Simulators .....................................................................................13

2.7 Wavelets .......................................................................................16

### III  METHODOLOGY

3.1 Template Design ............................................................................23

3.2 Development of the simulator model ..............................................40

3.3 Output Display .............................................................................43
3.4 Data Analysis ........................................................................................................45

IV RESULTS ...................................................................................................................46

V DISCUSSION ............................................................................................................50

5.1 Probable sources of error ....................................................................................50

5.2 Conclusions .........................................................................................................52

5.3 Future Work ........................................................................................................53

REFERENCES .............................................................................................................55

APPENDICES .............................................................................................................58

APPENDIX A. HARDWARE USED BY NASA FOR DATA ACQUISITION ...............59

APPENDIX B. PROGRAM IN TURBO C FOR D/A CONVERSION BY AD7237 ....60

APPENDIX C. SIMULATOR INSTRUCTION MANUAL .............................................62

APPENDIX D. PROOF OF IRB APPROVAL OBTAINED BY NASA AMES RESEARCH CENTER .................................................................71

APPENDIX E. COPY OF THE UNIVERSITY OF AKRON IRB REGISTRATION FORM (EXCLUDING THE STUDY FROM IRB REVIEW) .................................................................73
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1</td>
<td>46</td>
</tr>
</tbody>
</table>

4.1 Error analysis for the five simulated signals ..........................................................46
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Four cycles of an Electrocardiogram</td>
<td>7</td>
</tr>
<tr>
<td>2.2</td>
<td>Blood Pressure</td>
<td>8</td>
</tr>
<tr>
<td>2.3</td>
<td>Respiratory curve</td>
<td>10</td>
</tr>
<tr>
<td>2.4</td>
<td>Photoplethysmogram</td>
<td>11</td>
</tr>
<tr>
<td>2.5</td>
<td>dZ/dt waves</td>
<td>13</td>
</tr>
<tr>
<td>2.6</td>
<td>Basis functions for Fourier and Wavelet Transforms</td>
<td>17</td>
</tr>
<tr>
<td>2.7</td>
<td>Wavelet analysis as a windowing technique</td>
<td>18</td>
</tr>
<tr>
<td>2.8</td>
<td>Continuous Wavelet Transform (CWT)</td>
<td>19</td>
</tr>
<tr>
<td>2.9</td>
<td>Single step wavelet decomposition</td>
<td>20</td>
</tr>
<tr>
<td>2.10</td>
<td>Multi-step wavelet decomposition and reconstruction</td>
<td>21</td>
</tr>
<tr>
<td>3.1</td>
<td>Display of the source data file</td>
<td>24</td>
</tr>
<tr>
<td>3.2</td>
<td>Original ECG signal</td>
<td>25</td>
</tr>
<tr>
<td>3.3</td>
<td>Biorthogonal wavelet (bior5.5)</td>
<td>26</td>
</tr>
<tr>
<td>3.4</td>
<td>Original ECG signal and its approximations</td>
<td>27</td>
</tr>
<tr>
<td>3.5</td>
<td>Reconstruction of the ECG signal using Approximations (A2)</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>Details (D2 and D1)</td>
<td></td>
</tr>
<tr>
<td>3.6</td>
<td>Wavelet filtered ECG template</td>
<td>29</td>
</tr>
<tr>
<td>3.7</td>
<td>ECG template (after shifting sample points)</td>
<td>29</td>
</tr>
</tbody>
</table>
CHAPTER I
INTRODUCTION

Simulation is the representation/duplication of some real thing, state of affairs or process by another system, usually called the simulator. Simulation can be performed using a hardware device or a simulation program or a combination of both. They are used in many contexts, including the modeling of natural systems or human systems in order to gain insight into their functioning. Other contexts include simulation of technology for performance optimization, safety engineering, testing, training and education. It is also used to show the eventual real effects of alternative conditions and courses of action. Key issues in simulation include acquisition of valid source information about the object of reference, selection of key characteristics and behaviors, the use of simplifying approximations and assumptions within the simulation, and fidelity and validity of the simulation outcomes [1].

There are various advantages of simulators, as outlined by Craig [2]. One of the primary advantages of simulators is their ability to provide users with practical feedback when designing real world systems. This allows the designer to determine the correctness and efficiency of a design before the system is actually constructed. Consequently, the user may explore the merits of alternative designs without actually physically building the systems. By investigating the effects of specific design decisions during the design
phase rather than the construction phase, the overall cost of building the system diminishes significantly. Another benefit of simulators is that they permit system designers to study a problem at several different levels of abstraction. By approaching a system at a higher level of abstraction, the designer is better able to understand the behaviors and interactions of all the high level components within the system and is therefore better equipped to counteract the complexity of the overall system. Simulators can be used as an effective means for teaching or demonstrating concepts to students. Such simulators dynamically show the behavior and relationship of all the simulated system's components, thereby providing the user with a meaningful understanding of the system's nature. It also permits students to speed up, slow down, stop or even reverse a simulation as a means of aiding understanding [2].

With advances in technology, new and better methods for teaching the practice of medicine and reinforcing best practices have been developed; medical simulation being one of the most exciting innovations in the field of health care. The use of simulation in medicine has increased markedly, in part due to greater awareness of the importance of patient safety. Medical simulation is a cross-disciplinary effort that brings together providers, including nurses, physicians, and allied health professionals across a variety of disciplines with computer scientists, researchers, educators, and human factor engineers. It allows individuals to review and practice procedures as often as required to reach proficiency without harming the patient [3]. Among the several advantages of medical simulation [4], a few of them are as follows:
• Presentation of uncommon but critical scenarios in which a rapid response is needed. To conduct systematic training about managing such critical events there is little alternative but to use simulation.

• Errors can be allowed to occur and reach their conclusion—in real life a more capable clinician would have to intervene—so participants can see the results of their decisions and actions.

• With mannequin-based simulators clinicians can use actual medical equipment, exposing limitations in the human-machine interface.

• Complete interpersonal interactions with other clinical staff can be explored and training in teamwork, leadership, and communication provided.

Currently, simulators are applied to research and development of tools for new therapies, treatments and early diagnosis in medicine. They allow educators to control the training environment, protect patients from harm and standardize assessments. Computer-based medical simulation provides a realistic and economical set of tools to improve and maintain the skills of health care providers, adding a valuable dimension to medical training similar to professional training in aviation, defense, maritime, and nuclear energy. Employing it can help move medicine from the old “see one, do one, teach one” method to a “see one, practice many, do one” model for success [3].
1.1 Objective of the study

Simulation, both physical and computer-based, has a rich history in support of medical education. Computer simulation of human disease and its treatment can in principle be tremendously useful in the education of both basic and clinical scientists. The objective of this research study is to develop a software program (using MATLAB\(^1\), Version 7.1 (R14) Service Pack 3) that simulates physiological signals such as electrocardiogram (ECG), blood pressure, respiration, photoplethysmogram (pulse oximeter tracing) and rate of change of cardiac impedance (dZ/dt). It eliminates the need of an actual patient/subject to be present while generating the signals. The simulator can assist in the process of medical education by being a visual learning tool and can aid in the purpose of diagnosis. Controllable changes can be introduced into the source (standard) signal, which will be extremely helpful in developing feature extraction algorithms of a minimum error rate [19]. This physiological simulator would be able to present learners with choices, facilitating a degree of learning by doing.

Specific objectives of the study are:-

1) Simultaneous simulation of different physiological signals besides the ECG, such as blood pressure, respiration, photoplethysmogram and time derivative of the impedance cardiogram (dZ/dt).

2) To use wavelet-based multi-resolution analysis to create templates used in the simulation, as they provide excellent time-frequency localized information which is

\(^1\) MATLAB is a registered trademark of The MathWorks, Inc.
achieved by varying the aspect ratio, that is, the width of the time window to the width of
the frequency band.

3) To develop a realistic artificial biomedical signal generator that is able to encompass
the range of signals observed for both normal and abnormal subjects.

4) Availability of simulated output in both analog and digital form.

5) To develop a user interface, making the simulator user friendly and user interactive.

1.2 Research Hypothesis

The simulator that has been developed can be used as a visual learning tool or to
assist in the process of diagnosis. The simulated signals are morphologically similar to
the actual signals obtained directly from the human body. This is validated by calculating
the mean squared errors (MSE) and the root mean square error (RMSE) between the two
signals. If the squared errors are small then the actual difference will be small as well.
Both quantitative and qualitative evaluations are necessary to determine if the difference
between the simulated physiological signals and the signals recorded from the human
body are considered to be clinically insignificant or not.
CHAPTER II
BACKGROUND

2.1 Electrocardiogram (ECG)

The recording of the electrical activity associated with the functioning of the heart is known as electrocardiogram. ECG is a quasi-periodic, rhythmically repeating signal synchronized by the function of the heart, which acts as a generator of bioelectric events [5].

The heart has four chambers: the upper two chambers called the atria, and the lower two chambers called the ventricles. The atria are thin-walled, low-pressure pumps that receive blood from the venous circulation. Located in the top right atrium are a group of cells that act as the primary pacemaker of the heart. Through a complex change of ionic concentration across the cell membranes, an extracellular potential field is established which then excites neighboring cells, and a cell-to-cell propagation of electrical events occurs [6]. The first ECG wave of the cardiac cycle is the P wave, which represents activation of the atria. Conduction of the cardiac impulse proceeds from the atria through a series of specialized cardiac cells (the A-V node and the His-Purkinje system). There is a short, relatively isoelectric segment following the P wave. Once the large muscle mass of the ventricles is excited, a rapid and large deflection is seen on the
body surface. The excitation of the ventricles causes them to contract and provides the main force for circulating blood to the organs of the body. This large wave appears to have several components. The initial downward deflection is the Q wave, the initial upward deflection is the R wave, and the terminal downward deflection is the S wave. The polarity and actual presence of these three components depend on the position of the leads on the body as well as multitude of abnormalities that may exist. In general, the large ventricular waveform is generically called the QRS complex regardless of its makeup. Typical amplitude of QRS is 1mV for a normal human heart. Following the QRS complex is another short relatively isoelectric segment. After this short segment, the ventricles return to their electrical resting state. And a wave of repolarization is seen as a low-frequency signal known as the T wave [7]. The normal wave pattern of an electrocardiogram is shown in Figure 2.1.

![Figure 2.1: Four cycles of an Electrocardiogram.](image)
2.2 Blood Pressure

Blood is pumped by the left side of the heart into the aorta, which supplies it to the arterial circuit. Due to the load resistance of the arterioles and capillaries, it loses most of its pressure and returns to the heart at a low pressure via highly distensible veins. The right side of the heart pumps it to the pulmonary circuit, which operates at a lower pressure. The heart supplies blood to both circuits as simultaneous intermittent flow pulses of variable rate and volume. The maximum pressure reached during cardiac ejection is called systolic pressure and the minimum pressure occurring at the end of a ventricular relaxation is termed as diastolic pressure. The mean arterial pressure over one cardiac cycle is approximated by adding one-third of the pulse pressure (difference between systolic and diastolic values) to the diastolic pressure. All blood pressure measurements are made with reference to the atmospheric pressure [5]. A typical blood pressure waveform is illustrated in Figure 2.2

![Blood Pressure Waveform](image2.2)

**Figure 2.2 Blood Pressure**
Blood pressure is the most often measured and the most intensively studied parameter in medical and physiological practice. It is a key source of information for determining hemodynamic state of the patient. By processing arterial blood pressure waveforms, one can track trends such as mean pressure and heart rate. It is also useful in estimating cardiac output, arterial compliance and peripheral resistance.

2.3 Respiratory Signal

Breathing or pulmonary ventilation is accomplished by expansion and contraction of the lungs. This is achieved (1) by upward and downward movement of the diaphragm and (2) by elevation and depression of the ribs to increase and decrease the anteroposterior diameter of the chest cavity. Inspiration is initiated by the diaphragm and supported by the external intercostal muscles. Expiration is generally a passive process achieved by the abdominal and the internal intercostal muscle. Respiratory rate is defined as the number of breaths per minute or, more formally, the number of movements indicative of inspiration and expiration per unit time. Respiratory rate is included among the four traditional vital signs, which most often has to be monitored during spontaneous breathing as well as during ventilator support [8]. In practice, the respiratory rate is usually determined by counting the number of times the chest rises or falls per minute. By whatever means, the aim is to determine if the respirations are normal, abnormally fast (tachypnea), abnormally slow (bradypnea), or nonexistent (apnea).
Control of respiration is due to rhythmical breathing. It can vary in certain circumstances such as during exercise. Normal resting respiration rates vary between 10 and 18 breaths per minute. Figure 2.3 shows a respiratory curve.

![Respiratory Curve](image)

**Figure 2.3 Respiratory Curve**

### 2.4 Photoplethysmogram (PPG)

Optical spectroscopic investigations of human tissue and blood reach back as far as the late nineteenth and early twentieth century, and Hertzman is widely credited with introducing PPG in 1937 [9]. Photoplethysmography is an optical technique for the measurement of variations in skin blood volume and perfusion. It can be transmissive or reflective. Typically the PPG signal can be obtained from the serial port of a pulse oximeter. Besides its possible capability to monitor HR, arterial blood oxygen saturation (SpO2) measurements are commonly derived from this non-invasive probe. The photoplethysmogram bears a strong resemblance to an arterial pressure waveform complete with dichrotic notch [5] as shown in Figure 2.4.

![PPG Signal](image)

**Figure 2.4 Photoplethysmogram**

Previous study has demonstrated that the characteristics of the photoplethysmogram pulse signal are body site specific (Tur et al. 1983), with pulses
from the various peripheral sites showing differences in pulse transit time, strength as well as shape and variation of each over time. Commonly used sites for detecting the pulse waveform include the finger, the ear lobe, and the foot.

The photoplethysmograph trace derives from the change of attenuation of the light energy either transmitted or reflected through the tissues over which the pulse oximeter has been applied. This variation in light received by the photodetector depends on the erythrocyte orientation and concentration, local blood velocity, separation of light source and detector, and arterial inflow and venous outflow [10]. The pulse volume was obtained by calculating the difference between the base volume, characterized by the valleys in the waveform, and the peak volume characterized by the peaks in the waveform.

![Photoplethysmogram](image)

Figure 2.4 Photoplethysmogram.
2.5 Impedance Cardiography and dZ/dt

If electrodes are placed to encompass the thorax, impedance changes reflecting cardiac activity are recordable with ease. Nyober, one of the pioneers in the use of electrical impedance to measure blood volume changes, developed what is now called the backslope or end-systolic extrapolation technique (1959) to obtain a value for the impedance change $\Delta Z$ that reflects the entry of blood between the potential-measuring electrodes when no outflow occurs. Because graphical extrapolation involves visual estimation of the steepest part of the immediate post peak impedance curve, it is often more convenient to employ electronic differentiation to identify this slope [11].

A correction method was developed by Kubicek et al. (1966) with the assumption that at the beginning of inflow to the interelectrode segment, outflow is minimal and inflow is maximal. Therefore forward extrapolation of the steepest part of the impedance pulse would provide an impedance change $\Delta Z$ that is corrected for outflow. Therefore the stroke volume $\Delta V$ entering the segment can be calculated by using the expression:

$$\Delta V = \rho \left( \frac{L}{Z_o} \right)^2 T \left( \frac{dZ}{dt} \right)_{\text{max}}$$

where $\rho =$ the resistivity of blood (Ω-cm),
$L =$ the separation (cm) between the two inner potential measuring electrodes;
$Z_o =$ the basal impedance between the potential measuring electrodes,
$\left( \frac{dZ}{dt} \right)_{\text{max}} =$ the maximum rate of change in impedance (Ω/sec), and
$T =$ the ventricular ejection time (see Figure 2.5)
Figure 2.5 illustrates the labeled dZ/dt recording. The A wave reflects atrial contractility. Ventricular ejection commences with the B wave and continues to the X wave, when the aortic valve closes. The pulmonic valve closes at Y; O identifies opening of the mitral valve. Rapid ventricular filling is associated with the Z wave. The ability of the B-X interval to identify the left ventricular ejection time T has been documented by Labibidi et al. (1970, 1971), Hill et al. (1976), and Colin (1982).

2.6 Simulators

A realistic synthetic ECG signal was generated based on three differential equations by McSharry et al. [12]. In this dynamic model, the operator could specify the mean and standard deviation of the heart rate, the morphology of the PQRST cycle, and the power spectrum of the RR tachogram. It generates a trajectory in a three-dimensional state space with co-ordinates \((x, y, z)\). Quasi-periodicity of the ECG is reflected by the movement of the trajectory around an attracting limit cycle of unit radius in the \((x, y)\)-plane. Each revolution on this circle corresponds to one RR-interval or heart beat. Inter-beat variation in the ECG is reproduced using the motion of the trajectory in the \(z\)-
direction. Distinct points on the ECG, such as the P, Q, R, S and T are described by events corresponding to negative and positive attractors/repellers in the $z$-direction. These events are placed at fixed angles along the unit circle given by $\theta_P, \theta_Q, \theta_R, \theta_S$, and $\theta_T$ [12]. The differential equations were integrated numerically using a fourth order Runge-Kutta method [13] with a fixed time step $\Delta t = 1/f_s$ where $f_s$ is the sampling frequency.

The existing ECG model was augmented by McSharry et al. [14] to generate a multiparameter synthetic biomedical signal generator capable of generating realistic ECG, BP and respiration with their associated couplings. BP waveforms were generated by adjusting the angle, amplitude and width variables in the differential equation until a realistic waveform resulted. The respiratory signal is simply the high frequency (HF) oscillation and was generated using only the HF contribution of the inverse Fourier Transform of a sequence of complex numbers with amplitudes of the power spectrum of the RR-intervals and phases randomly distributed between 0 and $2\pi$ [14].

Modifications of the above published models were made for generating 24-hour versions of these waveforms [15]. Initially, a 24 hour tachogram was built from a series of stationary states with prescribed means, variances and low frequency/high frequency (LF/HF) ratios. This was then coupled to the three ordinary differential equations to generate 24-hour signals which have statistical similarities with real data on many scales.
Open source C, Matlab and Java code for these models is available from Physionet.

A piecewise synthesis of ECG was achieved by Burke and Nasor [17]. These were based on the second order equations in the square root of the cardiac cycle time $T_{R-R}$ of the form $AT_{R-R}^{1/2} + BT_{R-R} + C$, to obtain the duration of each individual component in an ECG which varies with heart rate in a non linear manner. The ECG profile generated was a realistic simulation of the true in vivo variation. The QRS complex was generated as a series of linear ramps with the S-wave having fixed amplitude of 25% of that of the R-wave. The P-wave and T-wave were generated from stored data files defining the morphology of these components of the signal. Intermediate isoelectric periods between individual waves are maintained as baseline levels. This simulator unit was built around the 80C31 microcontroller (Intel Inc.). The operating program was contained in an 8 KB erasable programmable read-only memory (EPROM) connected to the microcontroller. The controller interfaces, via a peripheral interface adapter chip for port expansion, with a keypad for input and a liquid crystal display (LCD) module. The output ECG signal was generated via a multi-level digital-to-analogue conversion unit.

Oosterom and Oostendrop created an interactive simulation program, named ECGSIM, wherein the user is allowed to make interactive changes to the timing of depolarization and repolarization on the ventricular surface, as well as changing the local source strength for studying the genesis of QRST waveforms [18]. It involves two models: a model of the bioelectric generator—that is, a source model – and a model for
describing the effects on the observed signals of the body tissues that surround the active
electric sources – a volume conductor model. The transfer factors between the electric
sources and the resulting potentials on the heart surface as well as on the body surface
were computed using a realistic thorax model. These transfer factors were then
implemented in a simulation program which produced ECG waveforms, potential maps
or movies [18]. The entire package is available from www.ecgsim.org.

An ECG simulation system was built in the SIMULINK environment by Josko
and Rak [19]. It included multiplicated pairs: parameterized pulse generator followed by
a low-pass filter (each pair for a different ECG wave), a summation block, and a module
introducing both low and high frequency interference. Modification of the pulse
generator parameters (amplitude, period, phase, duty cycle) enables one to perform ECG
signal simulation in a very wide range of changes, making it possible to simulate a
standard (normal) ECG signal as well as the abnormal ones. Then it was implemented for
testing of the developed QRS detection algorithm, based on the time-frequency analysis
method [19].

2.7 Wavelets

A wavelet is a waveform of effectively limited duration that has an average value
of zero. Fourier analysis represents signals as linear combinations of sine and cosine
waves, and therefore the representations are localized in frequency, not in time [20]. The
wavelet analysis uses linear combinations of basis functions (wavelet), localized both in time and frequency.

\[ f(t) = \text{Linear combination of basis functions (wavelets)} \]

\[ = \sum_{j,k} b_{j,k} w_{j,k}(t) \]

where \( j \) and \( k \) are dilation (or scale) and translation indices respectively, and \( w_{j,k} \) denotes a wavelet basis which is a collection of functions obtained by dilating and translating a scaling function \( \phi \) and a mother wavelet \( \psi \). By combining the scaling and wavelet functions, we can represent any class of signal as:

\[ f(t) = \sum_{k=-\infty}^{\infty} c_k \phi(t-k) + \sum_{k=-\infty}^{\infty} \sum_{j=0}^{\infty} d_{j,k} \psi(2^j t - k), \]

where the indices \( j \) and \( k \) are stated as above, and \( c_k \) and \( d_{j,k} \) denote the scaling and details coefficients respectively [20].

Comparing wavelets with sine waves, which are the basis of Fourier analysis, it has been observed that sinusoids do not have limited duration – they extend from minus to plus infinity. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric (Figure 2.6).

![Figure 2.6: Basis functions for Fourier and Wavelet Transforms. Courtesy Misti et al. [21]](image-url)
Signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid, just as some foods are better handled with a fork than a spoon. Wavelet analysis is a windowing technique with variable sized regions. It allows the use of long time intervals where more precise low-frequency information is required, and shorter regions where high-frequency information is desired (Figure 2.7).

![Wavelet analysis as a windowing technique. Courtesy Misti et al. [21]](image)

Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss; aspects such as trends, breakdown points, discontinuities in higher derivatives, and self similarity. Furthermore, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or denoise a signal without appreciable degradation. There exists many different types of wavelet transforms all starting from the basic formulas [22].

A. The continuous wavelet transform (CWT) and

B. The discrete wavelet transform (DWT)

Within the discrete wavelet transform we distinguish further between
B1. Redundant discrete systems (frames).

B2. Orthonormal (and other) bases of wavelets.

CWT and DWT are different with respect to the set of scales and positions at which each operates. CWT operates at every scale and is also continuous in terms of shifting, i.e. the analyzing wavelet is shifted smoothly over the full domain of the analyzed function (Figure 2.8).

![Figure 2.8: Continuous Wavelet Transform (CWT). Courtesy Misti et al. [21]](image)

For DWT’s scales and positions are chosen based on powers of two, and hence called dyadic scales and positions. What distinguishes the Wavelet Transform (WT) from the Short Time Fourier Transform (STFT) is the multi-resolution nature of the analysis [20]. This property enables the WT to zoom in on singularities and makes it very attractive for the analysis of transient signals. Although the time and frequency resolution problems are results of a physical phenomenon (the Heisenberg uncertainty principle) and exist regardless of the transform used, it is possible to analyze any signal by using an alternative approach called the multi-resolution analysis (MRA). MRA, as implied by its name, analyzes the signal at different frequencies with different resolutions.
MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. [This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations]. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by upsampling and downsampling. The wavelet transform decomposes a discrete signal into two subsignals of half its length. One subsignal is a running average; called approximation or trend; the other subsignal is a running difference; called detail or fluctuation. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. The filtering process, at its most basic level would be of form as illustrated in Figure 2.9.

Figure 2.9: Single step wavelet decomposition. Courtesy Misti et al. [21]
The original signal, $S$, passes through two complementary FIR filters and is downsampled by two to produce two DWT coefficients, coefficients of approximations and coefficients of details. This is one step decomposition or DWT or wavelet analysis. Reconstruction of the signal $S$ is done by upsampling the DWT coefficients by a factor of two and then passing them through high and low pass filters. It is also called IDWT or synthesis or reconstruction. A multi-step analysis-synthesis process can be represented as shown in Figure 2.10. The wavelet coefficients obtained after decomposition are modified (de-noising or compression) before performing the reconstruction step.

Several wavelet basis function types are available in the literature. Some of these are the Haar’s, Daubechies’, coiflets, symlets, bi-orthogonal wavelets, etc. Although Haar’s has a compact support, it does not have good time-frequency localization. It is unsuitable for representing classes of smoother functions due to its discontinuities. The most widely used wavelet is the Daubechies’ basis function. The Haar’s filter is best
suited to represent step signals of piecewise constant signals, whereas the Daubechies’ filter is better for smoother signals [20].

Some of the desirable properties of the basis functions are good time-frequency localizations, various degrees of smoothness (number of continuous derivatives), and large number of vanishing moments (ensures maximum number of zeros of the polynomial at the highest discrete frequency).

It is well known in the subband filtering community that if the same FIR filters are used for reconstruction and decomposition, then symmetry and exact reconstruction are incompatible (except with the Haar wavelet). Therefore, with biorthogonal filters, two wavelets are introduced instead of just one. One set is used to decompose the signal and the other to reconstruct it. Further, they allow certain desirable properties to be incorporated separately within the decomposition wavelet and the reconstruction wavelet.

For example, \( \psi_{m,n} \) and \( \bar{\psi}_{m,n} \) can have different numbers of vanishing moments. If \( \psi_{m,n} \) has more vanishing moments than \( \bar{\psi}_{m,n} \), then decomposition using \( \psi_{m,n} \) suppresses higher order polynomials and aids data compression. Reconstruction with the wavelet \( \bar{\psi}_{m,n} \) with fewer vanishing moments leads to a smoother reconstruction. This can sometimes be a useful property, for example in signal and image processing.
The necessity of a simulator is to replicate a task environment with sufficient realism to serve a desired purpose. Medical simulators are essential resources for developers and evaluators of algorithms and systems for analysis of physiological data [23]. This chapter describes the steps involved in developing a simulator of physiological signals which includes the electrocardiogram, blood pressure, respiratory signal, photoplethysmogram and derivative of the impedance cardiogram (dZ/dt). The software program for the simulator was developed using MATLAB 7.1. This project can be broadly classified into the following segments:

- Designing templates for signals that need to be simulated.
- Development of the patient/subject simulator.
- Display of the simulated signals in either the analog or digital form.

3.1 Template Design

Simulation of the five physiological signals was done by creating templates. The template served as a basic pattern (or a guide). It was used to replicate the physiological signals, by being a substitute for the real physiological signals. Each of the simulated signals has a template. To create a template, a previously recorded physiological signal
was selected. This cycle should have no baseline drift and preferably less noise. For this project, the data file obtained from NASA Ames Research Center was used to obtain the previously recorded electrocardiogram, blood pressure, respiratory signal, photoplethysmogram, and time derivative of cardiac impedance. The data file contained fifteen channels of raw physiological data which were acquired at a sampling rate of 250 samples per second per channel as shown in WinDaq (Figure 3.1).

![Figure 3.1 Display of the source data file.](image)

The channels acquired consisted of right and left finger pulse volumes, respiratory signal, electrocardiogram, temperature, right and left toe pulse volumes, skin conductance.

---

2 See Appendix D for proof of IRB approval obtained by NASA Ames Research Center.

3 WinDaq is a registered trademark of DATAQ Instruments, Inc,
level, right and left arm electromyogram, right and left leg electromyogram, blood pressure signal, rate of change in impedance (dZ/dt) and basal impedance (Zo). The information on the hardware used for data acquisition is provided in Appendix A.

ELECTROCARDIOGRAM (ECG) TEMPLATE DESIGN

Figure 3.2 shows one complete cycle of electrocardiogram (ECG) which was selected from the NASA data file. This ECG cycle was wavelet transformed using the biorthogonal wavelet (‘bior5.5’).
analysis as opposed to the convention of using two filters (one scaling and one wavelet function). These compactly supported biorthogonal wavelets are symmetrical and the reconstruction and decomposition functions and filters are close in value making possible exact reconstruction of any signal. ‘5.5’ in bior5.5 denote vanishing moments for reconstruction and decomposition filters are 5 respectively. The effective length of the decomposition filter is 9; the effective length of reconstruction filter is 11.

Figure 3.3 Biorthogonal Wavelet (bior5.5)  
Courtesy Misti et al. [21]

A wavelet transform decomposes the signal into approximations, A (low frequency) and details, D (high frequency). The details or fluctuations are the ones which
usually have the noise content of the signal. On having performed multiresolution analysis, the second level of approximations was selected with a few detail coefficients to create an ECG template. As can be seen from Figure 3.4, the second level approximation (A2) is smoother when compared to the original ECG signal.

A few details (from the first and the second levels) are added to the second level ECG approximations (A2), in order to obtain the correct amplitude for the R peak in the QRS complex, as shown in Figure 3.5. The ECG template and the ECG signal obtained after shifting the sample points is as shown in Figure 3.6 and Figure 3.7. The QRS complex of the ECG signal is used as a gating signal, wherein the blood pressure, respiratory signal,
photoplethysmogram (PPG) and the derivative of cardiac impedance are synchronized with the R peak of the ECG signal.

Figure 3.5 Reconstruction of the ECG signal using Approximations (A2) and Details (D2 and D1)
Figure 3.6: Wavelet filtered ECG template.

Figure 3.7: ECG template (after shifting sample points).
BLOOD PRESSURE (BP) TEMPLATE DESIGN

A similar approach that was used for creating the ECG template was used in designing the template for the blood pressure signal. Figure 3.8 shows once cycle of the blood pressure signal that was selected from the NASA data file. Wavelet filtering of the above signal using biorthogonal ‘bior5.5’ decomposes the signal into approximations and details. The first, second and third approximations are plotted over the original blood pressure signal, as seen in Figure 3.9.

Figure 3.8: Original BP signal.
The third approximation (A3) is smooth as compared to the original blood pressure signal, and most of the noise was also removed from the original signal by wavelet filtering. The QRS complex in the ECG signal corresponds to the depolarization of the ventricles. Immediately after ventricular contraction begins the ventricular pressure rises abruptly, causing the atrioventricular valves to close. Then an additional 0.02 to 0.03 seconds are required for the ventricle to build up sufficient pressure to push the semilunar (aortic and pulmonary) valves open against the pressures in the aorta and pulmonary artery. When the pressure rises slightly above 80 mm Hg, blood immediately flows out of the ventricle into the aorta and thence into the systemic distribution arteries [24]. This delay of 0.02 to 0.03 seconds between the R peak and the diastolic point (pressure of 80 mm Hg) is modeled as a delay of 200 milliseconds in this simulator, as
the pressure reading in the source data file was recorded from the wrist of the right hand. This takes into effect the time taken by the blood to flow from the aorta to the arteries of the right hand. Therefore, the blood pressure template has this delay accounted for as shown in Figure 3.10.

RESPIRATORY SIGNAL TEMPLATE DESIGN

The respiratory system in the human body facilitates oxygenation of the blood with a constant removal of carbon dioxide and other gaseous metabolic wastes from the
circulation. It also helps maintain the acid-base balance of the body through the efficient removal of carbon dioxide from the blood. Respiratory rate (RR), the number of breaths per minute, is one of the four important vital signs required to assess the most basic body functions. The rate can be calculated from the respiratory waveform by determining the elapsed time between successive inspiratory cycles. Figure 3.11 illustrates a section of the respiratory waveform selected from the NASA data file.

![Respiratory waveform](image)

**Figure 3.11: Original respiratory signal.**

On wavelet filtering the original respiratory waveform, the third level approximation (A3) was chosen to form the template. The multi-resolution analysis by
the biorthogonal wavelet got rid of noise present in the original signal. The respiratory signal template is shown in Figure 3.12.

Figure 3.12: Respiratory signal template.

PHOTOPLETHYSMOGRAM (PPG) TEMPLATE DESIGN

The photoplethysmogram signal is pulsatile in nature. It can be used to determine the finger pulse volume by calculating the difference between the base volume characterized by the valleys in the waveform and the peak volume characterized by the peaks in the waveform. Figure 3.13 shows one such cycle of the PPG signal taken from the NASA data file. Figure 3.14 illustrates the wavelet filtered PPG signal. The average elapsed time between the valley of the PPG waveform and R peak of the ECG signal was determined to be 320 milliseconds. Hence, the PPG template is designed as shown in Figure 3.15.
Figure 3.13: Original PPG signal.

Figure 3.14: Wavelet filtered PPG signal (Third approximation, A3).
dZ/dt TEMPLATE DESIGN

The change in thoracic impedance relative to time (dZ/dt) is an important parameter required in determining the stroke volume and cardiac output of the heart. The change in impedance (ΔZ) is measured from the baseline impedance (Zo) which is the overall thoracic resistance to flow of electrical current. Figure 3.16 depicts one such cycle of the dZ/dt waveform which was selected from the NASA data file and the wavelet filtered second level approximation of the signal. A delay of 168 milliseconds between the R peak of the ECG signal and the peak of dZ/dt signal was incorporated into this simulator model (Figure 3.17).
Figure 3.16: Original dZ/dt signal and its approximations.

Figure 3.17: dZ/dt template.
The other designed templates were for ventricular flutter (VF), premature ventricular contraction (PVC), and left bundle branch block (LBBB). The source file for creating these templates was obtained from among the 40 databases present in the MIT-BIH database\(^4\) provided by MIT and Boston’s Beth Israel Hospital [25]. Here the MIT-BIH Arrhythmia Database (mitdb) for left bundle branch block, the MIT-BIH ST Change Database for premature ventricular contraction and the CU (Creighton University) Ventricular Tachyarrhythmia Database (cudb) for ventricular flutter are used.

Left bundle branch block (LBBB) occurs when transmission of the cardiac impulses are delayed or fail to be conducted along the conducting fibers of the left bundle branch. Thus, the left ventricle depolarizes slowly by means of cell-to-cell conduction that spreads from the right ventricle to the left ventricle. This results in the characteristic ECG pattern shown in Figure 3.18. LBBB also disrupts the normal, coordinated and simultaneous distribution of the electrical signals to the two ventricles. The QRS which represents the spread of the heart’s electrical impulses across the right and left ventricles is said to widen during LBBB. Since the pattern of the spreading of the electrical impulse is abnormal, the QRS complex is also misshapen.

PVC’s are a very common form of arrhythmia. It is a form of irregular heartbeat in which the ventricle contracts prematurely. During a PVC, the ventricle electrically discharges (and contracts) prematurely before the normal electrical discharges arrive.

\(^4\) See Appendix E for a copy of the University of Akron IRB registration form (excluding the study from IRB review)
from the SA node. These premature discharges are due to electrical irritability of the heart muscle of the ventricles. Immediately after PVC, the electrical system of the heart rests. This resetting causes a brief pause in the heartbeat. PVC is characterized by wide QRS complexes (Figure 3.19).

Figure 3.18: ECG depicting a left bundle branch block.

Figure 3.19: ECG signal with a PVC.
Ventricular flutter (VF) is a form of rapid ventricular tachycardia in which the ECG assumes a regular undulating pattern without distinct QRS complex and T waves. There is no P wave visible and the frequency is between 180 and 250 beats per minute, as seen in Figure 3.20.

![Figure 3.20: Ventricular Flutter.](image)

3.2 Development of the simulator model

The software for the simulator was created using MATLAB and its Wavelet Toolbox (Version 3.0.3). An array consisting of instantaneous heart rate values, calculated from the ECG signal in the NASA data file, was generated. The heart rate varied from a minimum of 67 beats per minute to a maximum of 94 beats per minute. Figure 3.21 shows the heart rate variations that were recorded in the array. This array represented instantaneous heart rate variations of a subject at rest. This same array could
be tailored to exhibit heart rate variations of a subject in sleep, doing exercises or any other physical activity.

![Heart Rate Variations](image)

**Figure 3.21:** Instantaneous heart rate variations obtained from the source data file.

Using the ECG template and the heart rate values in this array, a series of ECG cycles was simulated using the resample command in MATLAB. All the other signals including the blood pressure, respiratory signal, PPG, and the dZ/dt signal were simulated simultaneously using their respective templates. The beginning of each of these signals was synchronized with the R peak of the ECG signal. Figure 3.22 shows the first ten seconds of simulated output of all five signals in MATLAB. A similar approach was used to simulate left bundle branch block beats, premature ventricular contractions and ventricular flutter. Figure 3.23 illustrates these abnormal ECG patterns. A detailed step by step instruction on the working of the simulator is provided in the Simulator Instruction Manual [Appendix C].
Figure 3.22: First ten seconds of simulated output.

Figure 3.23: Simulated output of abnormal ECG patterns.
3.3 Output Display

All the simulated signals are obtained as 1-D arrays in MATLAB. They are then given to a digital-to-analog converter in a data file of DADiSP\textsuperscript{5} format (*.dat). A computer program written in Turbo C++\textsuperscript{6} (version 3.0) was used to read this data file [26]. This program provided the required number of channels with data as output, through a digital-to-analog (D/A) converter at a required steady rate. [Appendix B]. The Industrial Computer Source D/A converter AOB x/12 card, which makes use of the 12 bit D/A converter AD7237 integrated circuit chip, was used for reading the digital data from the file. Each analog output channel is configured for a bipolar range of -5V to +5V. Data are transferred into outer registers a byte at a time and then transferred into inner registers a word at a time. The analog outputs are updated using the automatic update mode, where each channel is updated individually when new data are written to the related high-byte base address.

The analog output becomes the input for an analog-to-digital (A/D) converter, DI-720. DI-720 Data acquisition Module manufactured by DATAQ\textsuperscript{7} Instruments uses a 16-bit A/D converter for high resolution measurement accuracy. The DI-720 features software programmable input measurement ranges of ±10V full scale at a gain of 1; ±5V full scale at a gain of 2; ±2.5V full scale at a gain of 4; and ±1.25V full scale at a gain of 8. In this study, a full scale range of ±5V at a gain of 2 was used for acquiring the

\textsuperscript{5}DADiSP is a registered trademark of DSP Development Corporation.

\textsuperscript{6}Turbo C++ is a registered trademark of Borland International, Inc.

\textsuperscript{7}DATAQ is a registered trademark of DATAQ Instruments.
simulated analog data. The five simulated signals obtained on WinDaq are illustrated in Figure 3.24, and the abnormal ECG signals are displayed in Figure 3.25.
3.4 Data analysis

A good simulator is judged by its ability to minimize the distortion while retaining all significant features of the signal. The distortion in reconstruction by wavelets has been computed by means of mean square error and root mean square error. In general, the errors are defined by

Mean square error (MSE) = \frac{1}{N} \sum_{i=1}^{N} (x_{or} - x_{sim})^2 \quad \ldots \ldots \ (1)

Root mean square error (RMSE) = \sqrt{MSE} \quad \ldots \ldots \ (2)

where \( x_{or} \) and \( x_{sim} \), are respectively, the original and the simulated signals of length \( N \).

These errors are measures to assess the accuracy of the simulation. Reconstruction with a low MSE (or RMSE) does not necessarily mean clinical acceptance. The crucial requirement is not to distort the diagnostic information in the physiological signals which is used by physicians.
CHAPTER IV

RESULTS

The results from the method proposed in the previous section are presented in this chapter. These include both qualitative and quantitative evaluation. The data points were tabulated in spreadsheets and difference scores were calculated between the original and the simulated physiological signals. In order to visually compare them, the original physiological signals are plotted with the wavelet simulated signals. (see Figure 4.1 through 4.5). Table 4.1 gives the mean square error values and root mean square error values calculated for each of the physiological signals.

Table 4.1: Error analysis for the five simulated signals.

<table>
<thead>
<tr>
<th>Physiological Signal</th>
<th>Mean Square Error (Volts)$^2$</th>
<th>Root Mean Square Error (Volts)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECG</td>
<td>0.0006</td>
<td>0.0245</td>
</tr>
<tr>
<td>BP</td>
<td>0.0011</td>
<td>0.0332</td>
</tr>
<tr>
<td>Respiration</td>
<td>$3.8355 \times 10^{-5}$</td>
<td>0.0062</td>
</tr>
<tr>
<td>PPG</td>
<td>0.0038</td>
<td>0.0616</td>
</tr>
<tr>
<td>dZ/dt</td>
<td>0.0006</td>
<td>0.0245</td>
</tr>
</tbody>
</table>

Mean square error and root mean square error are frequently used measures of difference between the values predicted by a model and the values actually obtained from the system being modeled. These differences are also called as residuals. Lower value of
error indicates less residual variance. It is also a measure to assess how well a method to reconstruct a signal performs relative to the original recorded signal.

Figure 4.1: Original and simulated Electrocardiogram.

Figure 4.2: Original and simulated Blood Pressure signals.
Fig 4.3: Original and simulated Respiratory signal.

Figure 4.4: Original and simulated Photoplethysmogram.
Performance of wavelet based algorithms may depend on the particular basis chosen for the signal reconstruction. The Biorthogonal family of wavelets exhibits the property of linear phase which is required for signal and image reconstructions. Using two separate wavelets for reconstruction and decomposition simultaneously provides perfect reconstruction while preserving length (orthogonality), good performance at boundaries (via linear phase symmetry) and high order of approximations (vanishing moments) [27]. By using the error values and visual judgment, it can be concluded that the proposed method of simulating physiological signals is a good fit to obtain physiological signals with clinically significant features.
CHAPTER V
DISCUSSION

Any real time processing requires an inflow of a continuous stream of data that would be acquired and processed. It was realized that it would not be feasible to have a human subject from whom data could be acquired every time a system was to be tested and evaluated [26]. Hence, the need for a simulator arises. Furthermore, in the research and education domain, the investigation of any signal recognition algorithm, the demonstration of rarely occurring physiological conditions, etc. require in general a programmable simulator [28]. This programmability implies necessarily that any physiological signal should be simulated by a simulator to suit user’s requirements. This chapter addresses the probable sources of errors in developing this simulator, with future work that could be done in this area.

5.1 Probable sources of error

This study involves two data conversions, one from digital to analog (using AD7237) and the other from analog to digital (using DI-720). The analog output error could be a combination of gain and offset error. Offset error is the deviation from the minimum voltage expected when the minimum code is applied. Gain error is the difference between the actual output voltage with a full scale input code and the ideal
voltage that should exist with a full scale input code [29]. The overall absolute worst case error may be calculated by summing these component errors.

A quantization error is always associated with any analog to digital converter. Quantization error is a round off error. It is caused due to the resolution of the A/D converter [26]. The resolution of any converter indicates the number of discrete values it can produce over the given range of analog values. For DI-720, with a resolution of 16 bits it can encode an analog input to one in 65,536 levels, since $2^{16} = 65,536$. Resolution can also be defined electrically, and expressed in volts. The voltage resolution for DI-720 is given by $\frac{FSR}{2^n}$, FSR is the full scale voltage range and n is the number of bits in the converter. With a dynamic range of 10 Volts (-5 to +5 Volts), the voltage resolution is calculated to be $\frac{10}{2^{16-1}} \approx 0.31 mV$.

The DI-720 series of instruments have a 16 bit A/D converter, but the maximum resolution that is obtained in this study using the WinDaq software is 14 bits. The two least significant bits are truncated to make the WinDaq software computationally efficient. This leads to truncation error in the values of the acquired data [26].

Selecting an appropriate gain factor in the WinDaq data acquisition software will produce a more accurate, higher resolution representation of the signal that is acquired. An increase in gain factor produces an increase in resolution. An increase in resolution allows for a more detailed representation of the signal [30]. A proper gain factor is
essential in the medical research area, to find changes or anomalies in the signals that may have otherwise been overlooked. In this case, a dynamic range of +5 to -5 Volts with a gain factor of 2 was used for each channel.

5.2 Conclusions

Overall, the proposed programmable simulation method was found to be effective in approximating and reproducing the true physiological signals. This method was successful in reducing noise and distortion present in the real measured signals and thus, provides highly accurate measurements. The salient features and benefits of the simulator designed in this study can be summarized as follows:

- It has pre-programmed scenarios, but also facilitates design and addition of new cases.
- The software approach is cheaper and easier to implement in a clinical environment than existing hardware approaches.
- Anatomically realistic: enabling a range of medical interventions to be practiced.
- Educational effectiveness: through providing highly realistic patient simulation training experiences for the practice of teamwork, leadership and communication skills.
- Multi-function use: facilitates training of a wide range of health care professionals encompassing all areas of patient care.
The use of wavelet based technique can also be extended to accomplish data compression and feature extraction for each of the simulated physiological signals. Wavelet-based multi-resolution analysis has gained popularity in the analysis of both stationary and non-stationary signals. The simulator output can be used to determine the functionality range of software routines (or algorithms) which determine the beginning and end points of a cycle, the minimum, maximum or mean signal values within the cycle or the rate at which the cycle repeats. The simulator is also a vital tool for testing algorithms that require reproducibility as algorithm refinements are proposed. Different phenomena that appear occasionally in the real signal can be reproduced repeatedly in the simulated one. Without a strictly reproducible test, one can never establish with certainty if an observed difference in the results of analysis is attributable to a difference in the analytic method or to a difference in the input data [23].

5.3 Future Work

The performance testing of any medical equipment is considered to be of utmost importance before evaluation in a clinical environment. Therefore, these tests could be performed with the help of a simulator which is capable of generating a wide variety of physiological signals in addition to the conventional ones [28]. The existing five channel simulator model can be augmented to generate a multi-parameter synthetic biomedical signal generator, capable of generating realistic physiological signals with their associated couplings. Abnormal morphological changes with time could be introduced in the ECG signal by using a parameter to control the position of any of the P, Q, R, S, or
events. This extension would be particularly useful for testing techniques which aim to
detect ST depression or elevation. With advancement in computer technology, simulators
can be developed which present complex, interactive, and lifelike experiences that assist
the process of medical education. The process of iterative learning through assessment,
valuation, decision making, and error correction creates a much stronger learning
environment than passive instruction.
REFERENCES


[15] Clifford G; McSharry P “Generating 24-Hour ECG, BP and Respiratory Signals with Realistic Linear and Nonlinear Clinical Characteristics Using a Nonlinear Model”.


[18] Oosterom A.Van; Oostendrop F.T “ECGSIM: an interactive tool for studying the genesis of QRST waveforms”.


## APPENDIX A

**HARDWARE USED BY NASA FOR DATA ACQUISITON**

<table>
<thead>
<tr>
<th>Signal</th>
<th>Body Location</th>
<th>Equipment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blood volume pulse 1</td>
<td>left index finger</td>
<td>NASA</td>
</tr>
<tr>
<td>Blood volume pulse 2</td>
<td>right index finger</td>
<td></td>
</tr>
<tr>
<td>Blood volume pulse 3</td>
<td>left toe</td>
<td>AFS-2</td>
</tr>
<tr>
<td>Respiration</td>
<td>Chest</td>
<td></td>
</tr>
<tr>
<td>Electrocardiography</td>
<td>chest-3 electrodes</td>
<td></td>
</tr>
<tr>
<td>Skin temperature</td>
<td>left little finger</td>
<td></td>
</tr>
<tr>
<td>Skin conductance</td>
<td>left palm - 2 electrodes</td>
<td></td>
</tr>
<tr>
<td>Electromyography 1</td>
<td>left forearm - 3 electrodes</td>
<td>J &amp; J Electronics</td>
</tr>
<tr>
<td>Electromyography 2</td>
<td>right forearm - 3 electrodes</td>
<td></td>
</tr>
<tr>
<td>Electromyography 3</td>
<td>left calf – 3 electrodes</td>
<td></td>
</tr>
<tr>
<td>Electromyography 4</td>
<td>right calf – 3 electrodes</td>
<td></td>
</tr>
<tr>
<td>Systolic blood pressure</td>
<td>right wrist</td>
<td>Colin Medical</td>
</tr>
<tr>
<td>Impedance cardiography</td>
<td>neck and thorax</td>
<td>Bioimpedance Inc.</td>
</tr>
</tbody>
</table>
#include <stdio.h>
#include <conio.h>
#include <dos.h>
#include <iostream.h>
#include <iostream.h>

#define BASE1 0x300
#define CH1 BASE1+0
#define CH2 BASE1+2
#define CH3 BASE1+4
#define CH4 BASE1+6
#define CH5 BASE1+8

void main(void)
{
    //******SETTING CARDS TO AUTOMATIC UPDATE MODE***************
    //******AND FULL SCALE VOLTAGE RANGE (see manual)**************
    inp(BASE1+10);
    inp(BASE1+15);
    //**************************************************************************
    char *fname;
    int n[4];
    float v;
    FILE *fp;
    cout<<"n\n***************************************************************";
    cout<<"n\nEnter the data file Name (with extension): ";
    cin>>fname;
}
fp=fopen(fname,"rb"); //Reads DaDisp Files
   // (Binary Interlaced float),
   // with header removed
   // (using Notepad).

if(fp==NULL) cout<<"n...could not open file..... ";
cout<<"n
n
n
*********************************************************

*.....Reading 5 channels of data from file :               *
*.....and sending to DAC cards (CH1 to CH5)               *
*n
************ Press any key to stop*************************

while(!kbhit())
{
   for(int i=0;i<=4;i++)
   {
      fread(&v,sizeof(v),1,fp);
      n[i]=(v/10)*4096+2048; //fullscale range of 10 V (+5 to -5)
         //and 2^12=4096 (since it is a 12 bit card)
         //refer to card manual for explanation.
   }

   outport(CH1,n[0]);
   outport(CH2,n[1]);
   outport(CH3,n[2]);
   outport(CH4,n[3]);
   outport(CH5,n[4]);

delay(4.457); // obtained by trial & error
}

fclose(fp);
cout<<"nBye";
APPENDIX C

SIMULATOR INSTRUCTION MANUAL

This section consists of detailed step by step instructions for using the simulator designed in this research study. Familiarity with basic programming in MATLAB and Turbo C++, and use of WinDaq for data acquisition is a required essential for implementation of the following steps:

1. Run the program `simulation.m` in the command window of MATLAB.
2. A pop-up menu appears; prompting the user to select one or all of the five physiological signals for display.
3. Once a selection is made the program creates a comma-separated value (CSV) data file (*.dat) which is stored in the current directory. The name of the file is based on the selection made by the user.
4. Import the CSV file in WinDaq Waveform Browser. This makes use of the file conversion utility that allows the user to convert other data files to the format used by the WinDaq Waveform Browser. The input format options are listed on the right side of the dialog box. The format option “Spreadsheet print file (ASCII)” should always be selected as the output from the MATLAB program is in that format. Save the file as a .DAT file under a name different from the name of the input file.
Once the file is saved, a command prompt dialog box is displayed indicating the number of channels that will be displayed on the WinDaq waveform browser and also requires a user input for the sampling frequency of each channel. Enter 250 as the sampling rate per channel (S/sec).

The second command prompt dialog box displays the units for each channel conversion. Press “Enter” to accept and complete the conversion.
After the conversion the physiological signals are displayed in WinDaq browser. At this step the user is required to select the entire data set using the time marker (TM) or by hitting the function key F4. Bring the data cursor to the beginning of the file and hit F4 till the bottom annotation line reads 0.000 SEC(TM).

Once the time is set to zero seconds move the data cursor to the end of the data file and save this entire selected data set using Save As option under the File menu. This makes possible exporting the selected data into a new data file with a variety of different storage formats. The output or export format options are listed on the right side of the following dialog box:
[9] Store the file under a new name different from the input file. The output should be DADisp format (radio button number 7) and Save As type (*.DAT). The two check boxes on the upper right hand corner of the dialog box should always be checked. The file is now saved in the DADiSP format as binary interlaced float. Click OK when the comment dialog box pops up; without entering any comments.

[10] Open this data file with Notepad to delete the header. The header in a DADiSP file would usually have the following information:

\[
\begin{align*}
\text{NUM\_SIGS} & \ 5 \\
\text{INTERVAL} & \ 0.004000 \\
\text{HORZ\_UNITS} & \ \text{SEC}
\end{align*}
\]
Save this file (with header removed).

[11] Transfer this file to the TC directory of the computer which has the AD7237 DAC cards installed on it. Run this same computer in the DOS mode to execute the program simulate.cpp.

[12] Once this program is executed, it asks the user to “Enter the data file name (with extension):”. Before the user inputs the data file name, the WinDaq Data Acquisition should be set to acquire the required number of channels, with sampling rate of 250 samples/sec/channel and a with a gain factor of 2 to use the ±5V range for each channel.

[13] On opening the WinDaq Data Acquisition software, set the sampling rate to a total of 1250 samples/sec (250 samples/sec x 5 channels = 1250 samples/sec), using the function key F3 or by clicking on Sample rate in the Edit menu.

[14] To activate the channel configuration, click on Channels in the Edit menu or double click on the Channels: field in the status bar. This displays the Channel selection grid. A check mark in the channel box indicates an enabled channel. Select the required number of channels for display.
Click on *Format Screen* in the *View* menu to change the current display to a *user-specified format* of 5 channels.

Click the left mouse button in the unselected channel’s annotation margin to select an analog channel for gain adjustment. A blue box will surround the Variable Waveform Assignment Indicator of the channel selected. The Variable waveform
Assignment Indicator displays the window number and the channel assigned to that window (X=Y; X=window number, Y= channel number).

[17] Click on Channel Settings in the Edit menu. This displays the Channel Settings dialog box:
Click on the gain factor of 2, where the full scale measurement range equals ± 5 volts. Repeat this for every channel.

[18] With all the settings done as per mentioned in the previous steps, the WinDaq software would be appear as shown below:

[19] Resuming the task of step [12], enter the data file name with the extension and hit enter. WinDaq Data Acquisition software will acquire the data as displayed below:
The data obtained in WinDaq can be recorded to be used for further analysis. Similar steps need to be conducted to display the three abnormal ECG signals with ventricular flutter, premature ventricular contraction and left bundle branch block beat. The file is stored as abnormal.m in MATLAB. The only difference would be instead of 5 channels, only 3 channels are required. The corresponding changes would have to be made while setting up the WinDaq Data Acquisition software (from step [13] onwards).
APPENDIX D

PROOF OF IRB APPROVAL OBTAINED BY NASA AMES RESEARCH CENTER

Bruce Taylor, Ph.D.
3508 Channing Cross Dr.
Stow, OH 44224

March 23, 2006

Dear Dr. Taylor:

Enclosed is a copy of the e-mail messages sent regarding NASA IRB approvals for your use of data collected as part of a NASA grant. Dr. Ralph Pelligrina, Chairman of the NASA-Ames Human Research Institutional Review board concurred that these data may be used as long as the subjects' identities are not revealed.

Hope this meets your board's approval.

Sincerely,

Patricia S. Cowings, Ph.D.
Research Scientist
Date: Tue, 14 Mar 2006 08:35:34 -0800
To: Ralph Pelligra <Ralph.Pelligra-1@nasa.gov>
From: pcowings <Patricia.S.Cowings@nasa.gov>
Subject: Re: IRB Permissions
Cc: Bruce Taylor <bruce@ghoticreek.com>

Thanks Ralph. I am sending a copy of your concurrence below to Bruce Taylor for his records.

Dr. Pat

At 08:27 PM 3/13/2006, you wrote:

Concur- providing the subjects cannot be identified, either directly or indirectly,...
R.Pelligra

Bruce

I believe that no additional IRB approvals are necessary if your students are using previously collected data and the files do not reveal the identity of the subject. Since you have
2 files already for subject O27, I've put the raw and processed files of the same subject that were collected during an Autonomic Function Test O27ANS on EOS.

These data were collected under The Morehouse Protocol HRI-242 "Telemedicine Applications of Autogenic-Feedback Training Exercise as a Treatment for Specific Patient Populations," which is scheduled to expire April 7, 2006. We will be closing out that protocol as the grant period has expired.
APPENDIX E

COPY OF THE UNIVERSITY OF AKRON IRB REGISTRATION FORM

(EXCLUDING THE STUDY FROM IRB REVIEW)