The Removal Of Motion Artifacts From Non-invasive Blood Pressure Measurements

2004

Paresh Thakkar
University of Central Florida

Find similar works at: https://stars.library.ucf.edu/etd

University of Central Florida Libraries http://library.ucf.edu

Part of the Electrical and Electronics Commons

STARS Citation

https://stars.library.ucf.edu/etd/248

This Masters Thesis (Open Access) is brought to you for free and open access by STARS. It has been accepted for inclusion in Electronic Theses and Dissertations by an authorized administrator of STARS. For more information, please contact lee.dotson@ucf.edu.
THE REMOVAL OF MOTION ARTIFACTS FROM NON-INVASIVE BLOOD PRESSURE MEASUREMENTS

by

PARESH PRAVIN THAKKAR
B.E. University of Mumbai, 2002

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Electrical and Computer Engineering
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Spring Term
2005
ABSTRACT

Modern Automatic Blood Pressure Measurement Techniques are based on measuring the cuff pressure and on sensing the pulsatile amplitude variations. These measurements are very sensitive to motion of the patient or the surroundings where the patient is. The slightest unexpected movements could offset the readings of the automatic Blood Pressure meter by a large amount or render the readings totally meaningless. Every effort must be taken to avoid subjecting the body of the patient or the patient’s surroundings to motion for obtaining a reliable reading. But there are situations in which we need Blood Pressure Measurements with the patient or his surroundings in motion; for instance in an ambulance while a patient is being transported to a hospital. In this thesis, we present a technique to reduce the effect of motion artifact from Blood Pressure measurements. We digitize the blood pressure waveform and use Digital Signal Processing Techniques to process the corrupted waveform. We use the differences in frequency spectra of the Blood Pressure signal and motion artifact noise to remove the motion artifact noise. The motion artifact noise spectrum is not very well defined, since it may consist of many different frequency components depending on the kind of motion. The Blood Pressure signal is more or less a periodic signal. That translates to periodicity in the frequency domain. Hence, we designed a digital filter that could take advantage of the periodic nature of the Blood Pressure Signal waveform. The filter is shaped like a comb with periodic peaks around the signal frequency components. Further processing of the filtered signal: baseline restoration and level shifting help us to further reduce the noise corruption.
TABLE OF CONTENTS

LIST OF FIGURES ........................................................................................................................................ vi

CHAPTER 1. INTRODUCTION .................................................................................................................. 1

1.1 Purpose of the Thesis .......................................................................................................................... 1

1.2 Effects of High Blood Pressure on the Human Body ......................................................................... 2

1.3 Blood Pressure Overview .................................................................................................................. 3

1.4 Overview of Human Heart and Arterial System .............................................................................. 4

1.5 Analysis of the Blood Pressure Waveform ...................................................................................... 7
  1.5.1 Pumping of the Heart ..................................................................................................................... 7
  1.5.2 Blood Flow and the Pressure Waveform ....................................................................................... 8

1.6 Techniques of Blood Pressure Measurement .................................................................................... 9
  1.6.1 Invasive Blood Pressure Measurement .......................................................................................... 9
  1.6.2 Manual Non-Invasive Blood Pressure Measurement ................................................................. 10
  1.6.3 Oscillometric NIBP Measurement ................................................................................................ 12
  1.6.4 Automatic Non-Invasive Blood Pressure Measurement ............................................................ 13

1.7 Problem under consideration .......................................................................................................... 15
CHAPTER 2. MODELING AND SIMULATION ................................................................. 17

2.1 Approach and Algorithm .............................................................................17

2.2 Modeling Noise .............................................................................................19

2.3 Generation of Blood Pressure Waveform .....................................................21

2.4 Frequency Domain Analysis using Fourier Transform .................................23

2.5 Frequency Domain Analysis of the Blood Pressure Waveform ...................24

2.6 Frequency Domain Analysis of the Noise Waveform ..................................25

2.7 Noise Corrupting the Blood Pressure Signal ................................................26

2.8 The Comb Filter ............................................................................................27

2.8.1 Example Application of a Comb Filter ......................................................29

2.9 Baseline Recovery Algorithm .......................................................................32

2.10 Curve Fitting Algorithm .............................................................................34

CHAPTER 3. SIMULATION RESULTS AND DISCUSSION ............................... 36

3.1 Simulation Methodology ...............................................................................36

3.2 Simulation Software Tool .............................................................................38

3.3 Effect of Motion Artifact Noise on Blood Pressure Waveform ....................40
3.4 Filtering using Rectangular-Shaped Comb Filter .......................................................41

3.5 Filtering using Sine-Shaped Comb Filter ................................................................45

3.6 Filtering using Improved Comb Filter ....................................................................50

CHAPTER 4. CONCLUSIONS AND FUTURE RESEARCH ..................................................56

APPENDIX: MATLAB CODE ..........................................................................................58

LIST OF REFERENCES .......................................................................................................66
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Anatomy of the Heart during the Systole and the Diastole</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>Schematic view of the Heart and the pathway of Blood through the Lungs and Internal Organs – The Pulmonary Circulation System</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>Schematic view of the Heart and the pathway of Blood through the rest of the Human Body – The Coronary and Systematic Circulation Systems</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>The Blood Pressure Waveform</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>The Sphygmomanometer</td>
<td>11</td>
</tr>
<tr>
<td>6</td>
<td>The Oscillometric Arterial Waveform</td>
<td>12</td>
</tr>
<tr>
<td>7</td>
<td>The Dinamap Pro 1000 Vital Signs Monitor from GE Medical Systems</td>
<td>13</td>
</tr>
<tr>
<td>8</td>
<td>Sample Automatic NIBP Waveform</td>
<td>14</td>
</tr>
<tr>
<td>9</td>
<td>Flowchart of Methodology</td>
<td>18</td>
</tr>
<tr>
<td>10</td>
<td>Simulated White Gaussian and Filtered Gaussian Noise and their respective PDF</td>
<td>20</td>
</tr>
<tr>
<td>11</td>
<td>Simulated Blood Pressure Waveform Samples in Time Domain</td>
<td>22</td>
</tr>
<tr>
<td>12</td>
<td>DFT of Blood Pressure Signal</td>
<td>25</td>
</tr>
<tr>
<td>13</td>
<td>Frequency spectrum of Gaussian noise and Low Frequency Noise</td>
<td>26</td>
</tr>
<tr>
<td>14</td>
<td>Effect of Motion Artifact Noise on Blood Pressure Waveform</td>
<td>27</td>
</tr>
<tr>
<td>15</td>
<td>Example of a Comb Filter using a Moving Average Filter</td>
<td>29</td>
</tr>
<tr>
<td>16</td>
<td>Example Application of a Comb Filter</td>
<td>30</td>
</tr>
<tr>
<td>17</td>
<td>Frequency Domain Observations while filtering noise corrupted pulse-train with comb filter</td>
<td>31</td>
</tr>
</tbody>
</table>
Figure 18: Demonstration of Baseline Shifting Algorithm ................................................................. 32
Figure 19: Demonstration of the Baseline Recovery Algorithm (zoomed in version of time
domain pulses) ........................................................................................................................... 33
Figure 20: Example of Curve Fitting .................................................................................................. 34
Figure 21: Block Diagram of Simulation Implementation ................................................................. 37
Figure 22: Engineering Analysis using the MATLAB programming language .................................. 39
Figure 23: Blood Pressure signal samples before and after Noise corruption .................................. 40
Figure 24: Frequency Characteristics of the Rectangular Filter ......................................................... 41
Figure 25: Time Domain Waveforms demonstrating the use of the Rectangular Comb Filter .... 42
Figure 26: Frequency Domain Waveforms demonstrating the use of the Rectangular Comb Filter
.......................................................................................................................... 43
Figure 27: Performance analysis of the Rectangular Comb Filter ...................................................... 44
Figure 28: Frequency Characteristics of the Sine Filter ................................................................. 46
Figure 29: Time Domain Waveforms demonstrating the use of the Rectangular Comb Filter .... 47
Figure 30: Frequency Domain Waveforms demonstrating the use of the Sine Comb Filter .... 48
Figure 31: Performance analysis of the Sine Comb Filter ............................................................... 49
Figure 32: Frequency Characteristics of the Improved Comb Filter .................................................. 51
Figure 33: Time Domain Waveforms demonstrating the use of the Improved Comb Filter .... 52
Figure 34: Frequency Domain Waveforms demonstrating the use of the Improved Comb Filter 53
Figure 35: Performance analysis of the Improved Comb Filter ....................................................... 54
CHAPTER 1. INTRODUCTION

1.1 Purpose of the Thesis

Blood Pressure is a very important parameter for estimation of human health. Various health indices, like properties of the arterial system, ventricular or vascular coupling parameters, heart rate, systolic and diastolic pressures, hardening of arteries, pulse wave velocity, arterial compliance, clogging of important blood carrying vessels etc., can be calculated from blood pressure measurements [1]. Considerable research has been dedicated towards effective measurement of Blood Pressure in various situations. Hence, a variety of methods are available for measuring and monitoring blood pressure. These methods can be broadly classified as Invasive and Non-Invasive.

Invasive techniques involve making incisions and inserting Blood Pressure measuring cannulae (thin flexible tubes) into the body [2]. Non-Invasive techniques involve some form of a cuff wrapped around a person’s arm that is inflated and deflated while monitoring the pulse oscillations. Non-Invasive techniques are preferred because of their inherent painless nature and also have been automated in order to free up a doctor’s attention for more important tasks. These techniques require the patient and the environment to be steady while the measurement is being taken since the sensor (manual or automatic) needs to be very sensitive to monitor pulse oscillations continuously while the cuff is being inflated and deflated [3]. Thus the smallest amount of vibration, motion or shivering can offset the readings. Also, we may need to measure
Blood Pressure in mobile environments, like in an ambulance or an airplane and the motion artifact induced by the vehicular motion may offset the readings. In this research effort, we have tried to minimize the effect of Motion Artifact on Non-Invasive Blood Pressure (NIBP) measurements. We have used Digital Signal Processing (DSP) techniques to process the NIBP signals.

1.2 Effects of High Blood Pressure on the Human Body

Studies on the harmful effects of High Blood Pressure indicate the following effects on the various important parts of the body [4].

**Arteries:** High Blood Pressure is generally responsible for hardening of arteries in the heart, brain, kidneys etc. This situation puts the heart under more stress to pump blood through the body.

**Brain:** Very high blood pressure can cause a weakened blood vessel in the brain to break. The bleeding of that vessel or formation of a blood clot due to it may cause a “Stroke”.

**Heart:** If the arteries bringing oxygenated blood to the heart muscle do not render enough oxygen to the heart, chest pain may occur. If the flow of blood is blocked, heart attack may occur. Congestive Heart Failure may also result if the heart cannot pump enough blood to the body.
Kidneys: High Blood Pressure can thicken and narrow blood vessels in kidneys, which reduces their filtration capabilities. Waste builds up in the blood processed by kidneys.

1.3 Blood Pressure Overview

Blood pressure is the force applied against the walls of the arteries as the heart pumps blood through the body. The pressure is determined by the force and amount of blood pumped and the size and flexibility of the arteries [5].

Figure 1: Anatomy of the Heart during the Systole and the Diastole

Systolic pressure is the maximum pressure in an artery (which carries blood from the heart) at the moment when the heart is beating and pumping blood through the body [5].
Diastolic pressure is the lowest pressure in an artery in the moments between beats when the heart is resting. Both the systolic and diastolic pressure measurements are important - elevation of either one (or both) constitutes high blood pressure (hypertension) [5].

1.4 Overview of Human Heart and Arterial System

The Human circulatory system consists of three major components: the Heart, the Blood, and the Vascular System. The Vascular System comprises of Pulmonary, Coronary and Systematic Circulation Systems.

Pulmonary Circulation system is responsible for blood circulation between the heart and lungs. Deoxygenated blood from the body enters the right atrium from where it flows through the tricuspid valve into the right ventricle (see Figure 2). Pulmonary Arteries run from the right ventricle to the lungs carrying deoxygenated blood, where blood gets purified and oxygenated. Four Pulmonary Veins, two from each lung, carry clean oxygenated blood from the lungs to the left atrium ([6] and [7]).
Coronary Circulation system is responsible for supplying blood to the heart itself. Blood reaches the left ventricle through the mitral valve (see Figure 2). When the ventricle contracts the mitral valve closes and the aortic valve opens up to the aorta. The left and right Coronary Arteries originate within the Aorta, just beyond the aortic valve, within the heart. These supply blood to every capillary that penetrate every portion of the heart. The capillaries later drain circulated blood into the right atrium ([6] and [7]).
Systematic Circulation system is the remainder of the arterial network. Blood from the main artery, the Aorta, flows through a branching network of arteries that lead to all organs of the body (see Figure 3). It finally flows into a system of capillaries which penetrate every part of the body. Contaminated Blood is brought back to the right atrium of the heart through the veins called Superior Vena Cava (from upper body parts) and the Inferior Vena Cava (from lower body parts) ([6] and [7]).
1.5 Analysis of the Blood Pressure Waveform

1.5.1 Pumping of the Heart

Ventricles in the heart pump the body through the various organs of the body. Ventricles are essentially closed chambers surrounded by a muscular wall as seen in Figure 1. The valves are designed to allow blood flow in one direction only and passively open and close in response to the pressure differences across them [10]. Ventricular pumping action occurs because the volume of the intra-ventricular chamber is cyclically changed by rhythmic and synchronized contraction and relaxation of the individual cardiac muscle cells that lie in circumferential orientation in the ventricular wall. As soon as the ventricular pressure exceeds the pressure in the pulmonary artery (right pump) or the aorta (left pump), blood is forced out of the chamber through a valve. This phase when the ventricular muscle cells are contracting is called the systole. When the ventricular muscles relax, the pressure in the ventricle falls below that in the atrium, the arterio-ventricular valve opens and the ventricle refills with blood: this phase being called the diastole. The outlet valves remain closed during this period since the arterial pressure is more than the intra-ventricular pressure.
1.5.2 Blood Flow and the Pressure Waveform

The Blood Pressure Waveform (see Figure 4) can be divided into five time relative points which help to determine the condition of the heart and arterial system. They are referred to in the waveform in Figure 4 as the Foot, First Shoulder, Second Shoulder, Aortic Valve Closure and the entire Pulse Duration.

At the beginning of the pumping cycle, the Left Atrium has already received fresh oxygenated blood from the lungs by virtue of the Pulmonary Veins of the Pulmonary Circulation System (see Figure 2). From the Left Atrium, the blood enters the Left Ventricle through the Mitral Valve (see Figure 3). The contraction of the heart at this point of time leads to pumping of the blood.
from the Left Ventricle into the Aorta, which is a major human artery. The heart begins to eject blood through the arteries after the foot of the pulse, marking the beginning of the Systole [11]. This leads to an increase in blood flow through the arteries of the body leading to an increase in the Blood Pressure. The pressure wave rises to an initial peak where the First Shoulder is marked. The pressure then proceeds to a Second Shoulder, typically the peak pressure value in elderly people. The First Shoulder marks the timing of peak flow, whereas the Second Shoulder relates to reflected waves. The end of blood ejection from the heart is associated with the closure of the aortic valve, which is often seen as a distinct notch on the aortic pressure pulse. After this phase, there is a gradual decline in the pressure during the Diastole, due to the absence of blood flow from the ventricle. The deoxygenated blood from all the capillaries flows through the major veins: the superior and the inferior vena-cavae, back to the Right Atrium through the Tricuspid Valve. From here, the blood flows into the Right Ventricle from where it is fed back to the Pulmonary Circulation System through the Pulmonary Artery.

1.6 Techniques of Blood Pressure Measurement

1.6.1 Invasive Blood Pressure Measurement

This is a very precise method of Blood Pressure Measurement. It involves direct Arterial Blood Pressure Measurement by placing a cannula needle in an artery (Radial, femoral, dorsalis pedis or brachial) [2]. The cannula must be connected to a sterile fluid-filled system, which is connected to an electronic patient monitor. Typically, saline-filled non-compressible tubing is
inserted into the artery. This tube is connected to a pressure-transducer on the other end, which displays the waveform on a scope [8].

These systems have significant advantages that the pressure monitoring is constant, from one heart-beat to the next and thus enables us to obtain a waveform of pressure against time. A variety of monitors, including single pressure, dual pressure and multi-parameter (pressure or temperature), are available for BP monitoring for Trauma, Critical care and Operating room conditions [2].

The readings recorded from these systems are acquired, digitized, displayed, stored and processed further to monitor arterial, central venous, pulmonary arterial, left atrial, right atrial, femoral arterial, umbilical venous, umbilical arterial, and intracranial pressures. Systolic, Diastolic and Mean Arterial Pressure (MAP) readings are displayed simultaneously for pulsatile waveforms (arterial and pulmonary arterial).

1.6.2 Manual Non-Invasive Blood Pressure Measurement

Manual NIBP measurement requires an inflatable cuff with a pressure gauge (sphygmomanometer) [9]. The inflatable cuff has to be worn around the arm (at heart level) and then inflated to a level greater than the expected blood pressure level. Then, while deflating the cuff, the brachial artery is monitored for sounds with the stethoscope. When the cuff reaches systolic pressure, a clear tapping sound is heard with the heart beat. As
the cuff deflates further, the sounds become quieter, but become louder again before disappearing altogether. The point at which the sounds disappear is the diastolic pressure.

![Figure 5: The Sphygmomanometer](https://example.com/figure5)

*Used with permission from Mr. Peter Selig – peter.selig@horton.ednet.ns.ca*

The sounds heard while measuring blood pressure in this way are called the Korotkoff sounds, and undergo 5 phases [9]:

- initial 'tapping' sound (cuff pressure = systolic pressure)
- sounds increase in intensity
- sounds at maximum intensity (cuff pressure = 1st diastolic)
- sounds become muffled (cuff pressure = 2nd diastolic)
- sounds disappear
1.6.3 Oscillometric NIBP Measurement

Blood Pressure can be measured using the Von Recklinghausen Oscillotonometer [9]. It is a device which allows the Mean Arterial Pressure to be read without a stethoscope. It consists of two overlapping cuffs; one large, one small; a large dial for reading pressure, a bleed valve and a control lever. The large cuff performs the usual function of the sphygmomanometer cuff. The smaller cuff amplifies the pulsations which occur as the larger cuff is deflated, so that instead of listening for the Korotkoff sounds, they are seen as oscillations of the needle on the pressure gauge. The arterial pressure waveform during the measurement process is shown in Figure 6.

![Figure 6: The Oscillometric Arterial Waveform](image)

To measure Blood Pressure using this device, the cuff needs to be worn round the arm and inflated. The bleed valve is adjusted to let the pressure fall and the control lever is pulled. As the cuff pressure approaches systolic, the needle begins to jump more vigorously. If the lever is let go at this time, the needle will display systolic pressure. The lever needs to be pulled forward again. As the pressure is reduced, the needle jumps more vigorously. If the lever is released at
the point of maximum needle oscillations, the dial will read the Mean Arterial Pressure. If it is released at the point when the needle jumps get suddenly smaller, the dial reads Diastolic pressure. Over a length of time, the arterial pressure waveform looks like Figure 6. The point of maximum amplitude is considered Mean Arterial Pressure.

1.6.4 Automatic Non-Invasive Blood Pressure Measurement

Figure 7: The Dinamap Pro 1000 Vital Signs Monitor from GE Medical Systems

Automatic devices essentially use the same principle as the oscillotonometer. They are electronic devices. A single cuff is wrapped around the patients arm, and is inflated to a level estimated to be greater than systolic pressure. The cuff is deflated gradually. A sensor then measures the tiny oscillations in the pressure of the cuff caused by the pressure pulse. Systolic Pressure reading is taken to be when the pulsations start, Mean Arterial Pressure reading is when they are maximal and the Diastolic Pressure reading is recorded when they disappear.
In Figure 8, Section 1 shows the Pulsatile Pressure generated due to the complete occlusion of the brachial artery. This section is highly representative of aortic activity. Section 2 occurs when the cuff pressure has reduced just below systolic pressure. This leads to an increased blood flow in the artery, thus causing an amplitude and phase shift in the pressure signal. In this section, the pressure is between the Systolic and MAP. Section 3 represents the condition when the blood flow pressure balances out with the cuff pressure. MAP is the average pressure in the artery and is noted at the point of maximum amplitude. Here, the decreasing cuff pressure is no longer sufficient to occlude the artery. This causes the magnitude of the pressure signal to decrease between the Mean and Diastolic Pressures. Section 4 indicates that the cuff pressure is too low to occlude the artery. Hence, blood flow is no longer implemented. The line dividing Sections 3 and 4 of the waveform marks the point where diastolic pressure is measured.

An Analog to Digital Converter (ADC) then digitizes the output of the sensor for direct display, further processing, storage, display as a waveform (Figure 4) and similar other purposes. These devices give fairly accurate readings of the pressure and reduce the work of the doctor or anaesthetist during emergencies.
There are important sources of inaccuracy [10]: -

1. Such devices tend to over-read at low blood pressure, and under-read very high blood pressure.
2. Correct cuff size is critical for accurate measurements.
3. This technique relies on a constant pulse volume. The patient’s arm should be still during measurement.
4. In a patient with an irregular heart beat, readings can be inaccurate.
5. Sometimes an automatic blood pressure measuring device inflates and deflates repeatedly "hunting" without displaying the blood pressure successfully. If the pulse is palpated as the cuff is being inflated and deflated the blood pressure may be estimated using palpation and the cuff pressure reading on the display.

1.7 Problem under consideration

Blood pressure is traditionally measured in stationary conditions, i.e. the patient is stationary and positioned in a relaxed manner in a stationary environment. There are a variety of situations in which Blood Pressure needs to be measured with the patient in motion such as while walking, running, exercising etc. Blood Pressure measurement may also be needed in a mobile Environment, for instance, in an ambulance, airplane etc.
As pointed out in the description of the Automatic Non-Invasive Blood Pressure Measurement Technique, the patient needs to be still while the measurement is being taken. In this thesis we present an approach to reduce errors caused by motion artifacts in the Non Invasive Blood Pressure measurement.

The approach is based on the fact that the frequency spectra of the Blood Pressure Signal and the Motion Artifact Noise are different. The Blood Pressure waveform is essentially a periodic waveform. Its frequency spectrum is also periodic in nature. A model of the Blood Pressure signal frequency spectrum is used to construct a filter which could weed out most of the noise energy. The filter then adapts itself to the acquired Blood Pressure Signal spectrum to provide a solution that conserves signal energy more effectively. Various filter iterations were performed and investigated for high noise rejection and better signal reproduction.
CHAPTER 2. MODELING AND SIMULATION

2.1 Approach and Algorithm

The approach taken for this research effort is of simulating the blood pressure waveform and the effect of motion artifact noise on it. The Blood Pressure waveform simulated herewith is an idealized form of the actual blood pressure waveform shown in Figure 4. The idea is being able to distinguish between the signal and noise using their frequency domain characteristics. Since the noise frequency characteristics are highly unpredictable due to the various kinds of sources possible that cannot be reliably used to design a filter for the signal. The blood pressure waveform is almost periodic and its frequency characteristics are much more predictable. Hence, we model the required filter using the blood pressure signal frequency characteristics and filter the noise frequency components out using Fourier analysis. The filtered signal may require post-processing in the time-domain before being converted to continuous form. After converting the processed signal to continuous form, we could extract useful information parameters like the blood pressure values, errors as compared to initial ideal values and performance of the filter in the presence of noise.
Figure 9, above, pictorially represents the methodology. The simulated blood pressure and noise signals are summed up in the time domain. This signal is analyzed in the frequency domain using Fourier analysis. A filter is constructed using the frequency characteristics of the ideal blood
pressure waveform and is applied to this corrupted signal. The filtered frequency spectrum is converted back to the time domain using Inverse Fourier Transform techniques. The signal is then modified in the time domain to remove remaining noise. Signal parameters and the filter performance can then be evaluated after making the time domain waveform continuous using envelope curve fitting.

2.2 Modeling Noise

For simulating motion artifact noise, two factors come into play: the distribution of the noise in the frequency spectrum and the amplitude. Motion artifact noise is inherently more prevalent at lower frequencies. Noise is simulated and added to the blood pressure pulses to simulate the effect of motion artifact on blood pressure measurement. Gaussian Noise has been used for simulation purposes since it closely resembles the noise distribution created by natural processes.

Motion artifact noise, induced due to the patient’s moving hand or body or a moving environment like a vehicle, is a low frequency signal. Hence, we use a low pass filter to attenuate higher frequency components of the simulated noise.
Figure 10: Simulated White Gaussian and Filtered Gaussian Noise and their respective PDF

Figure 10, above, shows the initial computer generated Gaussian Noise in the first plot. The adjoining plot shows the Gaussian nature of the noise through a histogram. The histogram shows that the nature of noise is Gaussian with a zero mean and standard deviation of unity. The third plot shows low pass filtered noise (these values are designed for a normalized BP value of 1; they are actually multiplied by 100 for realistic BP measurement plots). The adjoining plot displays a histogram of the filtered noise to prove the Gaussian nature of the noise. We can see a 20 dB drop in magnitude due to the low pass filtering.

The design of the first order low pass filter is discussed below. In the s-domain, the transfer function of an analog first order low-pass filter with cutoff frequency $\omega_c$ is:
Using the Bilinear Transformation to convert a continuous filter to a discrete IIR Filter:

\[
H(s) = \frac{1}{1 + \frac{s}{\omega_0}}
\]  

Using the Bilinear Transformation to convert a continuous filter to a discrete IIR Filter:

\[
s = \frac{2}{T} \left( \frac{1-z^{-1}}{1+z^{-1}} \right)
\]  

Consequently, the equivalent digital filter is:

\[
H(z) = \frac{Y(z)}{X(z)} = \frac{1}{1 + \frac{2}{T\omega_0} \left( \frac{1-z^{-1}}{1+z^{-1}} \right)}
\]  

This yields the following in time domain after manipulation \((z^{-1}X(z) \Rightarrow x_{n-1})\):

\[
y_n = \frac{1}{1 + \frac{T\omega_0}{2}} \left[ (x_n + x_{n-1}) \frac{T\omega_0}{2} + y_{n-1} \left( 1 - \frac{T\omega_0}{2} \right) \right]
\]  

2.3 Generation of Blood Pressure Waveform

The Blood Pressure waveform, as seen in Figure 8, is repetitive in nature. The shape of the waveform is close to a sinusoid with its minimum near the diastolic pressure value and maximum near the systolic pressure value.
Figure 11: Simulated Blood Pressure Waveform Samples in Time Domain

Figure 11, above, shows the Blood Pressure waveform used in our simulation. It is a plot of the blood pressure values in mmHg (millimeters of Mercury) measured over time period of about 1 second. It is generated in digitized form (sampled at 256 samples per second) by modulating a pulse train with a sinusoid swinging between assumed diastolic pressure value of 60 mmHg and systolic pressure value of 100 mmHg. This closely resembles an actual blood pressure waveform. We use three blood pressure cycles (three systoles and three diastoles) to provide enough data points for the simulation.

As illustrated in Figure 11 above, Systolic pressure is measured as the maximum value of the curve within a beat period. Diastolic pressure is measured as the minimum value of the curve.
within a beat period. The Mean Arterial Pressure (MAP) value is calculated using the following formula:

\[ \text{MAP} = \frac{2 \times \text{Diastolic pressure} + \text{Systolic pressure}}{3} \]  

(5)

2.4 Frequency Domain Analysis using Fourier Transform

Discrete Fourier Transform is a technique to view the frequency information of discrete-time signals. A finite duration sequence \( x(n) \) of length \( L \) has a Discrete Fourier Transform:

\[ X(\omega) = \sum_{n=0}^{L-1} x(n) \cdot e^{-j\omega n}, \quad 0 \leq \omega \leq 2\pi \]  

(6)

\( X(\omega) \), the Discrete Fourier Transform, is continuous in the interval \( 0 \leq \omega \leq 2\pi \). For manipulating the frequency information in software, we need discrete values of the frequency information. Hence, we use the discrete form of the Fourier Transform, i.e. sample the Fourier Transform itself at discrete values of frequency. The Discrete Fourier Transform (DFT) of a finite-energy discrete-time signal \( x(n) \), obtained by sampling \( X(\omega) \) at equally spaced frequencies \( \omega_k = \frac{2\pi k}{N}, \ k = 0,1,2,...,N-1 \), where \( N \geq L \), is defined as:

\[ X(k) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j\frac{2\pi kn}{N}}, \quad k = 0,1,2,...,N-1 \]  

(7)

Physically, \( X(k) \) represents the frequency content of the discrete-time signal \( x(n) \). Thus \( X(k) \) is a physical decomposition of \( x(n) \) into its frequency components. This analysis helps us to determine distribution of the energy in a waveform in the frequency domain.
If the nature of the frequency characteristics of the signal waveform is known, a model of that
\( \tilde{X}(k) \) is used to construct a filter that would reject everything but the signal frequency
components. A point to be noted here is that the model is just an estimate of the signal frequency
characteristics and might be very different from a real signal’s frequency spectrum. The aim here
is to achieve the best possible Signal to Noise Ratio (SNR) with the least signal distortion.

The filtered signal spectrum \( X'(k) \) is converted back to the time domain using the following
Inverse Discrete Fourier Transform (IDFT) relation:

\[
x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X'(k) \cdot e^{j2\pi kn/N}, \quad n = 0,1,2,\ldots,N-1
\]  

(8)

### 2.5 Frequency Domain Analysis of the Blood Pressure Waveform

This section deals with studying the blood pressure waveform in the frequency domain. The
blood pressure waveform is repetitive in nature. In the frequency domain, the simulated blood
pressure waveform translates to the spectrum shown in Figure 12.
As we can observe in Figure 12, the nature of the spectrum is like a SINC waveform. This is contributed by the time domain train of sampling pulses. The blood pressure waveform essentially modulates the sampling pulses in the time domain. Hence the energy around each component of the SINC waveform is contributed by the time domain blood pressure waveform.

2.6 Frequency Domain Analysis of the Noise Waveform

This section deals with analyzing the noise frequency domain characteristics. We start with white Gaussian noise. White Gaussian noise has a flat magnitude spectrum; i.e. the magnitude response for all frequencies is almost the same.
Figure 13: Frequency spectrum of Gaussian noise and Low Frequency Noise

Figure 13, above, shows the result of low pass filtering on the noise spectrum. It is a plot of the noise magnitude with respect to frequency. To simulate the effect of motion artifact noise, the simulated noise is attenuated to a very low frequency of about 10 Hz.

### 2.7 Noise Corrupting the Blood Pressure Signal

The blood pressure signal samples are noise corrupted with the simulated motion artifact noise in the time domain. This is done by adding the simulated noise samples to the samples of the signal waveform in the time domain.
Figure 14: Effect of Motion Artifact Noise on Blood Pressure Waveform

Figure 14 above shows the effect of introducing the motion artifact noise. The first plot shows the effect in the time domain and the second plot shows the effect in the frequency domain.

2.8 The Comb Filter

To filter out the noise in the frequency spectrum, we need a filter that would pass maximum signal and least noise. The nature of the sampled blood pressure waveform frequency spectrum suggests that the filter has to have pass-bands at the signal’s harmonics and stop-bands elsewhere. A Comb filter is a filter with that kind of nature. It has periodically spaced pass-
bands. The spacing, width and gain of the pass-bands are the parameters of the comb filter that can be adjusted as per the signal quality.

A comb filter can be created by taking an FIR filter with system function:

$$H(z) = \sum_{k=0}^{M} h(k) \cdot z^{-k}$$  \hfill (9)

By replacing $z$ by $z^L$ in the FIR filter, where $L$ is a positive integer, the new FIR filter has a system function:

$$H_L(z) = \sum_{k=0}^{M} h(k) \cdot z^{-kL}$$  \hfill (10)

If the frequency response of the original FIR filter is $H(\omega)$, the frequency response of the above FIR filter is:

$$H_L(\omega) = \sum_{k=0}^{M} h(k) \cdot e^{-jkL\omega} = H(L\omega)$$  \hfill (11)

Thus the frequency response characteristic $H_L(\omega)$ is simply an $L$ – order repetition of $H(\omega)$ in the range $0 \leq \omega \leq 2\pi$.

An example of a comb filter constructed as a repetition of the moving average filter:

$$y(n) = \frac{1}{M+1} \sum_{k=0}^{M} x(n-k)$$  \hfill (12)

will have its transfer function:

$$H_L(z) = \frac{1}{M+1} \frac{1 - z^{-L(M+1)}}{1 - z^{-L}}$$  \hfill (13)
Hence, the frequency response will be:

\[ H(\omega) = \frac{1}{M+1} \frac{\sin[\omega L(M+1)/2]}{\sin(\omega L/2)} e^{-j\omega M/2} \]  

(14)

Figure 15: Example of a Comb Filter using a Moving Average Filter

2.8.1 Example Application of a Comb Filter

As an example of an application of a comb filter, below is a waveform of a pulse train without noise labeled as Uncorrupted Pulses.
Figure 16: Example Application of a Comb Filter

In Figure 16 above, the first plot shows a pulse-train in the time domain. Gaussian Noise generated in MATLAB is added to the pulses to generate the waveform labeled as Noise Corrupted Pulses. The third plot shows the result of comb filtering in the frequency domain. The frequency domain operations are discussed in detail below with plots.
As seen in Figure 17 above, the magnitude spectrum of the pulse-train signal $|X_{IN}(\omega)|$ is a SINC waveform as per the first plot labeled as FFT of Uncorrupted Pulses. Low frequency Gaussian noise can be seen in the second plot labeled as FFT of Noise Corrupted Pulses ($|X_{CORR}(\omega)|$). A comb filter is applied to the frequency spectrum of the corrupted signal waveform. The resulting magnitude spectrum after the filter $|Y(\omega)|$ is shown in the waveform labeled as Filtered Pulses.
This section deals with a technique used to correct any baseline shifts on a sampled signal in the time domain. Low frequency noise components may go unfiltered since they are embedded into the signal’s frequency spectrum. This leads to offsets in the time domain, which shift up the baseline of the filtered waveform. The signal effectively seems to be riding on a low frequency sinusoidal waveform as seen in Figure 18.

Hence an algorithm has been developed to achieve baseline restoration by manipulating the signal amplitude in the time domain. The approach behind the algorithm is that the amplitude...
should be of zero value when the sampling pulse is absent. Due to the low frequency noise, the signal is offset by a particular amount during each sampling interval.

Figure 19, above, demonstrates the Baseline Recovery algorithm. The amount by which the signal is offset during the sampling period when the sampling pulse is absent is averaged out over that time frame as seen in the figure. This average is then subtracted from the signal amplitude for that entire sampling period.
2.10 Curve Fitting Algorithm

The next step is to fit a curve on the processed sampled signal in order to obtain values of blood pressure parameters like the systolic pressure and the diastolic pressure. Curve fitting is implemented using Polynomial Fitting functions (‘polyfit’ and ‘polyval’) available in MATLAB.

Figure 20: Example of Curve Fitting

Figure 20, above, demonstrates curve fitting on a sinusoid. The POLYFIT command finds the coefficients of a polynomial $p(x)$ of degree $n$ that fits the data, $p(x(i))$ to $y(i)$, in a least squares sense. The above figure is of the sinusoid given by:

$$ y = \sin(5x) + \cos(8x) , \quad x = 0,0.1,\ldots,\pi $$

(16)
The polynomial generated by the POLYFIT function with a parameter of 12 for the polynomial degree was:

\[ p = 5.6672 \cdot x^{12} - 106.37 \cdot x^{11} + 870.14 \cdot x^{10} - 4067.7 \cdot x^9 + 11974 \cdot x^8 - 23057 \cdot x^7 + 29228 \cdot x^6 \\
- 23942 \cdot x^5 + 12105 \cdot x^4 - 3462.9 \cdot x^3 + 474.35 \cdot x^2 - 22.771 \cdot x + 1.0276 \]  

(17)

Then the POLYVAL command evaluates the polynomial of degree n at each value of x required to generate a continuous curve, which we see as the fitted curve in Figure 20 above.
3.1 Simulation Methodology

For simulating the effect of motion artifact on blood pressure measurement, the signal and the noise were generated in software. These were then processed using a digital filter, again, simulated in software. Parameters like error, mean error for several different cases of Signal to Noise Ratio (SNR), standard deviation of error for several different cases of Signal to Noise Ratio were calculated by comparing the final filtered signal against the initially assumed data. Performance can be easily estimated using those graphs.
Figure 21: Block Diagram of Simulation Implementation

Figure 21 shows the sequence of actions performed to demonstrate generation of the signal, addition of motion artifact, frequency domain filtering and time domain adjustments. The generated signal pulses and simulated Gaussian noise are summed up in the time domain to generate a corrupted signal. This frequency domain representation (Discrete Fourier Transform) of this signal is calculated using the Fast Fourier Transform algorithm. A comb filter is then constructed using the frequency characteristics of this signal. That filter is applied to the signal in the frequency domain to generate the DFT of the filtered signal. The time domain equivalent of the filtered signal is then calculated using the Inverse Fast Fourier Transform algorithm. This signal is further processed in the time domain using the Baseline Restore algorithm discussed previously. A curve is fitted around this processed waveform, which represents the continuous
form of the blood pressure signal. Diastolic Pressure and Systolic Pressure are measured from this curve and the Mean Arterial Pressure is calculated from these values using equation (5). These measured and calculated values are then compared to those from the original signal to determine the amount of error.

3.2 Simulation Software Tool

The simulation was implemented using MATLAB as the simulation software. MATLAB was chosen because it is optimized to perform engineering and scientific calculations [12]. The software implements the MATLAB programming language, which provides a very extensive library of predefined functions to facilitate technical programming. It offers advanced matrix mathematics, plotting tools, noise generators and such other features that are needed for this simulation.
Figure 22: Engineering Analysis using the MATLAB programming language

Figure 22, above, shows an Engineering analysis being implemented using the MATLAB programming language. In the background is the program editor window, where the user can enter a script file using the MATLAB programming language. The programming style and format are similar to the C programming language. In the foreground, we see three output windows, which in the above example depict the Eye-Diagram and the Scatter-Plot, both of which are useful tools in the analysis and design of communication systems. The MATLAB software generates figures like these from available data using inbuilt routines which generate the necessary user interfaces and interact with the operating system to display an output figure or a graph.
3.3 Effect of MotionArtifact Noise on Blood Pressure Waveform

The blood pressure waveform was generated by modulating a pulse train with a sinusoid. Gaussian noise samples were generated using a random number generator in MATLAB. The noise samples were added to the signal in the time domain.

![Blood Pressure Signal Samples](image)

Figure 23: Blood Pressure signal samples before and after Noise corruption

Figure 23, above, shows the effect of low frequency motion artifact noise (simulated Gaussian noise) on the blood pressure signal. The first plot displays the uncorrupted sampled blood pressure signal. The lower plot displays the distortion introduced by adding simulated low frequency motion artifact noise samples with a zero mean and a standard deviation of about 30 to the blood pressure samples. The 3 dB frequency of the low pass filter is designed to be at about
10 Hz. This helps maintain an SNR value of 11 dB. SNR values are varied between 5 dB and 30 dB while evaluating the performance of the filter.

3.4 Filtering using Rectangular-Shaped Comb Filter

The rectangular-shaped filter offers a unity gain in its pass-bands and it attenuates the signal in the stop-band.

![Figure 24: Frequency Characteristics of the Rectangular Filter](image)

Figure 24, above, shows the transfer function of the rectangular comb filter over a small range of frequencies. It is a plot of the filter gain $H(\omega)$ against the radian frequency $\omega$ over the band
0 radians to 0.0183\pi radians. The waveform similarly extends up to \pi radians. The comb passbands are placed at equal intervals so as to match with the signal’s harmonics as seen in Figure 12.

![Figure 25: Time Domain Waveforms demonstrating the use of the Rectangular Comb Filter](image)

Figure 25, above, demonstrates the use of the Rectangular shaped Comb Filter (shown in Figure 24) in the time domain. The y-axis represents the blood pressure amplitude in mmHg with respect to time on the x-axis. The first plot represents the uncorrupted blood pressure waveform. The second plot shows the effect of adding simulated motion artifact noise (Gaussian Noise with standard deviation of about 30 and 3 dB frequency of 10 Hz) to the blood pressure signal. The third plot is the Rectangular Comb filtered signal. The last plot is the Baseline adjusted...
waveform. The envelope around the pulses in the last plot is the outcome of curve-fitting applied to that plot.

Figure 26: Frequency Domain Waveforms demonstrating the use of the Rectangular Comb Filter

Figure 26, above, demonstrates the frequency analysis of the performance of the Rectangular Comb Filter. The y-axis on all the plots represents the magnitude of the corresponding frequency representation $|X_{\text{any}}(\omega)|$ against the radian frequency $\omega$ on the x-axis. The first plot shows the Discrete Fourier Transform of the uncorrupted signal. The second plot shows the effect of noise addition in the frequency domain. The third plot is the result of Rectangular Comb filtering in the frequency domain.
Figure 27: Performance analysis of the Rectangular Comb Filter

Figure 27, above, is used to evaluate the performance of the Rectangular Comb Filter. Each plotted point on the graphs is the mean of 10,000 simulations run at that particular SNR value, for 16 such SNR values. This is done to average out the effect of noise using 10,000 randomly generated sets of computer generated noise values. The first two plots are the Error Mean and Error Standard Deviation percentage of the Mean Arterial Pressure (MAP) for different values of the SNR in decibels. MAP itself is derived from the Systolic and the Diastolic values. The third and fourth plots show the Error Mean and the Error Standard Deviation percentage of the Systolic Pressure Measurement (against different values of SNR in dB) with respect to the initial systolic pressure values assumed. The fifth and sixth plots show the Error Mean and the Error Standard Deviation percentage of the Diastolic Pressure Measurement (against different values
of SNR in dB) with respect to the initial diastolic pressure values assumed. The values are calculated in accordance with the following equations:

\[
%Error = \left( \frac{\text{Theoretical Value} - \text{Measured Value}}{\text{Theoretical Value}} \right) \times 100
\]  

\[
%Error_{\text{Mean}} = \frac{1}{10000} \times \sum_{10,000} %Error
\]  

\[
%Error_{\text{StdDev}} = \left( \frac{1}{10000} \times \sum_{10,000} (\%Error - %Error_{\text{Mean}})^2 \right)^{\frac{1}{2}}
\]

The above equations are used for all three types of pressure values. Theoretical Values are those derived from the initial uncorrupted data. Measured values are obtained from the filtered signal. We observe that the error, in general, tends to decrease with increasing SNR.

### 3.5 Filtering using Sine-Shaped Comb Filter

The sine comb filter offers a sinusoidal shaped pass-band around each harmonic of the signal waveform. This filter is same as the rectangular comb filter except for the shape of the pass-band.
Figure 28: Frequency Characteristics of the Sine Filter

Figure 28, above, shows the transfer function of the Sine Comb filter over a small range of frequencies. It is a plot of the filter gain $H(\omega)$ against the radian frequency $\omega$, between 0 radians and $0.0183\pi$ radians. The waveform extends similarly up to $\pi$ radians. The comb pass-bands are placed at equal intervals so as to match with the signal’s harmonics as seen in Figure 12. The shape of each sinusoidal pass-band is given by the following equation:

$$H(k) = \frac{1}{M+1} \left( \sin \left( \frac{k-1}{N} \frac{\pi (M+1)}{2} \right) \cos \left( \frac{k-1}{N} \frac{\pi M}{2} \right) - i \sin \left( \frac{k-1}{N} \frac{\pi M}{2} \right) \right), k = 0, 1, 2, \ldots, N-1 \quad (21)$$

This sinusoidal template is placed at equal distances across the frequency spectrum to generate a comb filter. There is infinite attenuation in the stop-band, i.e. beyond the comb-width.
Figure 29: Time Domain Waveforms demonstrating the use of the Sine Comb Filter

Figure 29, above, demonstrates the use of the Sine-shaped Comb Filter (shown in Figure 28) in the time domain. The y-axis represents the blood pressure amplitude in mmHg with respect to time on the x-axis. The first plot represents the uncorrupted blood pressure waveform. The second plot shows the effect of adding simulated motion artifact noise (Gaussian Noise with standard deviation of about 30 and 3 dB frequency of 10 Hz) to the blood pressure signal. The third plot is the Sine Comb filtered signal. The last plot is the Baseline adjusted waveform. The envelope around the pulses in the last plot is the outcome of curve-fitting applied to that plot.
Figure 30: Frequency Domain Waveforms demonstrating the use of the Sine Comb Filter

Figure 30, above, demonstrates the frequency analysis of the performance of the Sine Comb Filter. The y-axis on all the plots represents the magnitude of the corresponding frequency representation $|X_{\text{any}}(\omega)|$ against the radian frequency $\omega$ on the x-axis. The first plot shows the Discrete Fourier Transform of the uncorrupted signal. The second plot shows the effect of noise addition in the frequency domain. The third plot is the result of Sine Comb filtering in the frequency domain.
Figure 31: Performance analysis of the Sine Comb Filter

Figure 31, above, is used to evaluate the performance of the Sine Comb Filter. Each plotted point on the graphs is the mean of 10,000 simulations run at that particular SNR value, for 16 such SNR values. This is done to average out the effect of noise using 10,000 randomly generated sets of computer generated noise values. The first two plots are the Error Mean and Error Standard Deviation percentage of the Mean Arterial Pressure (MAP) for different values of the SNR in decibels. MAP itself is derived from the Systolic and the Diastolic values. The third and fourth plots show the Error Mean and the Error Standard Deviation percentage of the Systolic Pressure Measurement (against different values of SNR in dB) with respect to the initial systolic pressure values assumed. The fifth and sixth plots show the Error Mean and the Error Standard Deviation percentage of the Diastolic Pressure Measurement (against different values of SNR in dB) with
respect to the initial diastolic pressure values assumed. These values are calculated using equations (18), (19) and (20).

Overall, we see some improvement in performance over the rectangular comb filter if we compare Figure 27 and Figure 31. The values of the percentage error mean and the percentage error standard deviation are smaller for the sine comb filter as compared to the rectangular comb filter. For example, the mean error percentage values for MAP vary between 35 and 0 % for the rectangular comb filter, whereas the range is only 20 to 0 % for the sine comb filter. Likewise, the maximum mean error percentage for the systolic values is 15 % for the rectangular comb and about 10 % for the sine comb.

3.6 Filtering using Improved Comb Filter

The rectangular and sinusoidal filters offer a flat or a continuous shaped response within each pass-band. This feature is not too effective for noise rejection within the pass-band. This comb filter is designed so as to adjust itself so as to reject noise in the pass-band. We take advantage the fact that motion artifact is low frequency noise. Also the blood pressure signal spectrum is repetitive in nature and hence all the harmonics are proportionally and equally distributed over the entire spectrum. Thus, if a filter is built using the characteristics of the signal at high frequencies, it would attenuate noise components even inside the comb pass-band.
Figure 32: Frequency Characteristics of the Improved Comb Filter

Figure 32 shows the frequency domain characteristics of the improved comb filter. We can see that the gain inside the pass-band is neither constant like the rectangular filter, nor continuous like the sinusoidal comb filters. It varies according to the presence of uncorrupted signal components. This is equivalent to a normalized signal spectrum template, which replaces the actual signal after being scaled by the corresponding frequency component contributed by the sampling pulses.
Figure 33: Time Domain Waveforms demonstrating the use of the Improved Comb Filter

Figure 33, above, demonstrates the use of the Improved Comb Filter (shown in Figure 32) in the time domain. The y-axis represents the blood pressure amplitude in mmHg with respect to time on the x-axis. The first plot represents the uncorrupted blood pressure waveform. The second plot shows the effect of adding simulated motion artifact noise (Gaussian Noise with standard deviation of about 30 and 3 dB frequency of 10 Hz) to the blood pressure signal. The third plot is the filtered signal. The last plot is the Baseline adjusted waveform. The envelope around the pulses in the last plot is the outcome of curve-fitting applied to that plot.
Figure 34: Frequency Domain Waveforms demonstrating the use of the Improved Comb Filter

Figure 34, above, demonstrates the frequency analysis of the performance of the Improved Comb Filter. The y-axis on all the plots represents the magnitude of the corresponding frequency representation $|X_{\text{any}}(\omega)|$ against the radian frequency $\omega$ on the x-axis. The first plot shows the Discrete Fourier Transform of the uncorrupted signal. The second plot shows the effect of noise addition in the frequency domain. The third plot is the result of Improved Comb filtering in the frequency domain.
Figure 35, above, is used to evaluate the performance of the Improved Comb Filter. Each plotted point on the graphs is the mean of 10,000 simulations run at that particular SNR value, for 16 such SNR values. This is done to average out the effect of noise using 10,000 randomly generated sets of computer generated noise values. The first two plots are the Error Mean and Error Standard Deviation percentage of the Mean Arterial Pressure (MAP) for different values of the SNR in decibels. MAP itself is derived from the Systolic and the Diastolic values. The third and fourth plots show the Error Mean and the Error Standard Deviation percentage of the Systolic Pressure Measurement (against different values of SNR in dB) with respect to the initial systolic pressure values assumed. The fifth and sixth plots show the Error Mean and the Error Standard Deviation percentage of the Diastolic Pressure Measurement (against different values

Figure 35: Performance analysis of the Improved Comb Filter
of SNR in dB) with respect to the initial diastolic pressure values assumed. These values are calculated in accordance with equations (18), (19) and (20). Overall, we see an improvement in performance over the rectangular and sine comb filters. The values of error are more consistent over the SNR range than in the previous cases.
We have presented an analysis of the effect of Motion Artifact on Blood Pressure measurement and an attempt to reduce the measurement error caused by the same. The signal is noisy at low frequencies, but the high frequencies have a higher SNR. The algorithm uses a Comb-shaped filter to reduce the motion artifact noise in the frequency domain. Three kinds of comb filters were used to filter out only the signal from the noise corrupted signal frequency spectrum. All of them had uniformly spaced pass bands along the spectrum of frequencies and infinite attenuation between the pass-bands.

The Rectangular comb filter reduced the noise to a large extent, but it had the shortcoming of a flat pass-band, which passed considerable amount of noise along with the signal. The maximum mean error percentage for the MAP values was observed to be about 35% for a rectangular comb filter and a corresponding standard deviation of about 20 %. The Sine comb filter was better in that respect, i.e. it attenuated noise in its pass-band. The problem with the Sine filter was that it also attenuated the signal frequency components along with the noise. The maximum mean error percentage for the MAP values was observed to be just about 20 % for the sine comb filter and a corresponding maximum standard deviation of about 20 %. An Improved Comb filter was designed to attenuate noise in its pass band without having to distort the signal frequency components. This filter is more consistent in its performance with respect to noise than the other filters, as it does not depend upon the nature and amount of spectral noise components in its pass
band. The maximum mean error percentage for the MAP values was observed to be less than 20 % for the improved comb filter and a corresponding standard deviation of about 20 %.

The comb filters have been designed to filter out pseudo-random computer generated Gaussian noise. Performance in the presence of an actual blood pressure signal with only motion artifact noise needs to be evaluated. Based on the results, the designed filter could be improved. Further, flexibility with respect to signal parameters; like the sampling rate, amount of signal data available, immunity to other types of noise (e.g. circuit noise, power supply noise, analog to digital converter noise, digital to analog converter noise etc.); needs to be designed for making this method useful with an actual device collecting blood pressure data. Also, for continuous monitoring applications (e.g. in a typical hospital environment), real time signal processing capability would be useful as the doctor might not always have all the time to allow the system to collect enough data points. Optimizations to improve execution speed, program memory required and volatile processing memory required would make the method more suitable for implementation in a mobile handheld or mountable device.
APPENDIX: MATLAB CODE
pack;
clear all;
clc;

pack; clear all; clc;

% Assumed Variables
data_size = 2^14;
duty_cycle = 20;
samples_per_second = 256;
SNR_db = -5;
Ts = 1/samples_per_second;
noise_freq = .05;
comb_width = 3;

% Derived Variables
pulses = zeros(data_size,1);
noise = zeros(data_size,1);
pulse_high = round(samples_per_second * (duty_cycle/100));

The above module initializes the variables required for implementing the simulation.

for i = 1 : samples_per_second : data_size,
    for j = 0 : pulse_high-1,
        if( (j+i)<=data_size ), pulses(j+i) = 1;end
    end
    for j = pulse_high : samples_per_second-1,
        if( (j+i)<=data_size ), pulses(j+i) = 0;end
    end
end

% Modulating the signal with a sine wave
for i = 1:data_size, modulator(i) = 0.6 + 0.4 *(sin(3*pi*i/data_size)).^2 ; end
pulses = pulses .* modulator);

The above module generates the blood pressure signal as a modulated train of pulses. The pulses are generated for a sample rate of 256 samples per second. These are modulated with a sine wave to simulate 3 blood pressure cycles within a second.

% Initializing the filtering process
cnt0 = 1;
K = 10000;
snr_vals = 16;
PSyserr = zeros(K, snr_vals);
PDiaserr = zeros(K, snr_vals);
MAPerr = zeros(K, snr_vals);
PSysactual = zeros(K, snr_vals);
PDiasactual = zeros(K, snr_vals);
MAPactual = zeros(K, snr_vals);
SNR_f = zeros(K, snr_vals);
seeds = 10000 * randn(K, 1); }
The above module initializes variables required for the filtering routine. These are values used for running the simulation 10,000 times over each of the 16 different SNR values used. These are initially assumed SNR values; the actual SNR values after filtering the noise are calculated and stored in a separate array SNR_f.

The above lines of code generate a progress bar display for the duration the program runs. With large data-sets, the program takes a very long time to produce results. Hence, this feature helps the programmer to be sure that the program is still running.

These lines of code set up the loop for the program to run for 16 different SNR values and to generate 10,000 noise data-sets for producing results that incorporate plenty of pseudo-random data-sets to avoid inconsistencies.

This module generates pseudo-random noise using randomly generated seed values. The noise is scaled at this point to satisfy the SNR specified at the beginning of the loop.
The above lines of code update the progress bar using the product of the number of SNR values, i.e. 16 and the number of iterations for each of those SNR values, i.e. 10,000.

```matlab
%%%% Filter Construction
noise_filt = zeros(data_size,1);
w0 = 2 * pi * noise_freq;
A = [1 - (1 - Ts*w0/2)/(1 + Ts*w0/2)]';
B = (Ts*w0/2)/(1 + Ts*w0/2) .* [1 1]';
oise_filt = filter(B, A, noise);
```

The above section filters the noise as discussed in section 2.2.

```matlab
%%%% Finding power values
noise_power =0;
oise_sqr = noise_filt .* noise_filt;
for i=1:data_size, noise_power = noise_power + noise_sqr(i); end
%%%% Finding effective SNR after noise filtering
sig_power =0;
sig_sqr = modulator .* modulator;
for i=1:data_size, sig_power = sig_power + sig_sqr(i); end
SNR_f(countMain, cnt0) = 10*log10(sig_power / noise_power);
```

These lines of code are used to calculate the effective SNR in dB after low-pass filtering the noise. The signal power and the noise power are found by summing the squares of their samples.

```matlab
%%%% Adding Low Pass filtered noise to the Pulses
corrupt_signal = zeros(data_size, 1);
corrupt_signal = pulses + noise_filt;
```

```matlab
%%%% Finding the Frequency Domain Representation of the signals
fft_signal = fft(pulses, 2^14);
fft_corr_signal = fft(corrupt_signal, 2^14);
```

These lines of code add the generated noise to the blood pressure signal pulses. We also calculate the Fourier Transforms of the original signal and the corrupted signal using the MATLAB inbuilt FFT function.

```matlab
%%%% Generating the Signal Template.
61
```

```matlab
n = 57;
c = 1;
for freq = 1 + 64*n - comb_width :1 + 64*n + comb_width ,
    filt(c) = fft_corr_signal(freq);
    freq = freq + 1;
c = c + 1;
end
filt = filt/max(filt);
```

```matlab
%%%% Applying Comb Filter
```

61
The above routine implements the Comb filter and applies it to the corrupted signal. This includes generating a signal template from the corrupted signal at one of its high frequency harmonics and scaling and pasting that template over the entire frequency spectrum. The filter is discussed in detail in section 3.6. The signal is also converted back to the time domain using the inbuilt Inverse-FFT function.

The above section of code is used to implement the Baseline-Recovery algorithm discussed in detail in section 2.9. This algorithm helps to filter out any more noise in the time-domain.
Envelope Curve Fitting onto the output waveform

envY = zeros(65,1); envX = zeros(65,1);
for i = 1 : samples_per_second - 1 : data_size-256,
    envY(round(i/samples_per_second) + 1) = max(new(i : i + samples_per_second-1));
    envX(round(i/samples_per_second) + 1) = i + samples_per_second/2;
end

l = length(envY);
warning off;
p = polyfit(envX, envY, 12);
warning on;
x2 = 1:data_size;
y2 = polyval(p,x2);

The above routine implements the Envelope curve fitting algorithm discussed in section 2.10.
This helps us to obtain a continuous signal waveform in the time domain from a digital signal, so that parameters like Systolic and Diastolic Pressures can be more accurately read from it.

Finding Pressure Values

PSystheo = max(modulator(4000:10000)) * 100;
PDiastheo = min(modulator(4000:10000)) * 100;
MAPtheo = (2 * PDiastheo + PSystheo)/3;

PSysactual(countMain, cnt0) = max(y2(4000:10000)) * 100;
PDiastactual(countMain, cnt0) = min(y2(4000:10000)) * 100;
MAPactual(countMain, cnt0) = (2 * PDiastactual(countMain, cnt0) + PSysactual(countMain, cnt0))/3;

PSyserr(countMain, cnt0) = abs(PSystheo - PSysactual(countMain, cnt0)) / PSystheo * 100;
PDiasserr(countMain, cnt0) = abs(PDiastheo - PDiastactual(countMain, cnt0)) / PDiastheo * 100;
MAPerr(countMain, cnt0) = abs(MAPtheo - MAPactual(countMain, cnt0)) / MAPtheo * 100;

This section calculates the values of the blood pressure parameters like the systolic, diastolic and MAP from the initially assumed data and the newly fitted curve. These values are compared to calculate Error in measurement as discussed in equations (18), (19) and (20).

end

cnt0 = cnt0 + 1;
end
close(waitHandle);
SNR = mean(SNR_f);

These lines mark the end of the nested loops being executed above.
This section creates a plot of the actual values of the systolic, diastolic and the MAP for 4 different SNR values over the 10,000 iterations.

This section creates a plot of the percentage errors of the systolic, diastolic and the MAP for 4 different SNR values over the 10,000 iterations.
Plotting the Error v/s SNR Performance Graphs for MAP, SP and DP

```matlab
figure('Name', 'Error values V/S SNR Values (ac)', 'NumberTitle', 'off');
MAPmean = mean(MAPerr);
PSysmean = mean(PSyserr);
PDiasmean = mean(PDiaserr);

MAPdev = std(MAPerr);
PSysdev = std(PSyserr);
PDiasdev = std(PDiaserr);

subplot(6,1,1), plot(SNR, MAPmean,'b*'); ylabel('Mean'); title('MAP Error vs SNR');
subplot(6,1,2), plot(SNR, MAPdev,'r*'); ylabel('Std Dev');
subplot(6,1,3), plot(SNR, PSysmean,'b*'); ylabel('Mean'); title('Systolic Error vs SNR');
subplot(6,1,4), plot(SNR, PSysdev,'r*'); ylabel('Std Dev');
subplot(6,1,5), plot(SNR, PDiasmean,'b*'); ylabel('Mean'); title('Diastolic Error vs SNR');
subplot(6,1,6), plot(SNR, PDiasdev,'r*'); ylabel('Std Dev'); xlabel('SNR (dB)');
```

This section creates a plot of the Percentage Mean (over the 10,000 iterations) of Error values and Percentage Standard Deviation (over the 10,000 iterations) of Error values for the systolic, diastolic and the MAP against all 16 SNR values.

Optional Code for plotting actual signals in time and frequency domains

```matlab
% subplot(3,1,1), stem(MAPerr); title('MAP Error');
% subplot(3,1,2), stem(PSyserr); title('Systolic Pressure Error');
% subplot(3,1,3), stem(PDiaserr);title('Diastolic Pressure Error');
% fprintf('
%.2f	%.2f	%.2f	%.2f', SNR_f, PSyserr, PDiaserr, MAPerr);
% figure(1); n = 1:xmax;
% subplot(4,1,1), plot(n, pulses(n)); axis([1 xmax min(pulses) max(pulses)]); title('UN-CORRUPTED PULSES'); grid on;
% subplot(4,1,2), plot(n, corrupt_signal(n)); axis([1 xmax min(corrupt_signal) max(corrupt_signal)]); title('NOISE CORRUPTED PULSES'); grid on;
% subplot(4,1,3), plot(n, abs(filtered_signal(n))); hold on; %plot(n, lp_filt_signal, 'm--'); axis([1 xmax min(filtered_signal) max(filtered_signal)]); title('FILTERED PULSES'); grid on;
% subplot(4,1,4), plot(n, abs(new(n)));hold on; plot(x2, y2, 'r-'); axis([1 xmax min(new) max(new)]); title('FILTERED PULSES'); grid on;
% figure;
% stem(abs(filt));axis([0 60 0 1.5]); title('NORMALIZED FILTER COEFFICIENTS'); grid on;
```

This is an optional block to provide the ability to plot time domain signals.

65
LIST OF REFERENCES


