Real Time Heart Rate Estimation From Severely Corrupted PPG Signal by Motion Artifact

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Declaration:

We hereby declare that research work titled "Real Time Heart Rate Estimation from Severely Corrupted PPG Signals by Motion Artifacts" is our own work. This paper has not been presented elsewhere for assessment. Where materials were used from other sources it has been properly acknowledged/ Referred.

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Abstract

Heart rate is a very important cardio logical data. It is considered to be one of the most important vital sign of a human body. Real time heart rate monitoring provides a great advantage over many aspects. PPG is a low cost and simple method to measure volumetric changes in blood vessel. It consist of vital physiological data along with heart rate. But PPG data gets extremely corrupted with motion artifacts, thus it is difficult to achieve clean PPG data which has been distorted by all sorts of motion. Our method of removing motion artifacts and estimating heart rate included 3 major parts. Adaptive noise cancellation based of four different motion artifact source. Peak tracking method from the four different heart rate estimate for every real time window. Last step was a systematic verification method so that the abrupt changes in PPG does not lead the estimation of heart rate in the wrong direction. Our method of estimating heart rate had an absolute error of about 1.73 beats per min, which is a satisfactory result. This method provides a very robust system in measuring heart rate and also promises result with unbelievingly high accuracy. It can be concluded that this method provides high level of accuracy which can be implemented in today’s high tech health monitoring devices.

Table of Contents

Abbreviation

PPG: Photoplethysmography

ECG: Electrocardiogram

MA: Motion Artifact

RLS: Recursive Least Squares

LMS: Least Mean Squared

RNS: Reference Noise Signal

ANC: Adaptive Noise Cancellation

BPM: Beats per Minute

HR: Heart Rate

LED: Light-emitting Diode

PD: Photo Detector

FIR: Finite Impulse Response

Chapter 1 | Introduction

Photoplethysmography is a technique which is used to noninvasively monitor the pulse of blood vessel [1]. It is obtained from pulse oximetry, an optical technique for measuring the blood volumetric changes in the blood vessel by illuminating the skin by an infrared light source and measuring the variations in light intensity reflected from the blood vessel passing through the skin tissue by a photodiode. The received light comes from different transverse path which can be classified into two different modes; received mode and transmitted mode. Transmitted mode can be explain when light transmits through the tissue and received by photodiode on the opposite side of the body. Whereas in the reflected mode both photodiode and light source are presented in same side of the body. The photodiode receives light reflected by the skin. Transmitted mode gives a relatively better signal as light needs to transmit through tissue. PPG consists of vital physiological parameters and for being low cost it has grown widely popular in no time among researchers. Now this technique is commonly used in medicals and hospitals mainly of its ability to monitor vital physiological signals of a human body, including oxygen saturation, heart rate and respiration rate [2]. The periodic spectrum of the PPG signal corresponding to the cardiac pattern makes it possible to extract heart rate from the PPG data. But the ones used in hospitals are not mobile and do not suffer from the noise artifacts present in the moving body. In hospitals patients are seated still while the assessment is being accomplished. In reality the rising of mobile health monitoring devices, demand for heart rate monitoring outside the medical setting in on the rise. Especially in ambulatory monitoring while the patient is being transported, the motion noise cannot be avoided. Also for an athlete, it is important to know if his body is fit enough to face the tough situations in the field or for athletic performance evaluation. The deterioration of the PPG signal due to motion artifacts is inevitable and in extreme case can lead to false abrupt medical readings which are highly unreliable. In presence of motion artifacts reliable reading are in fact has huge importance [3]. Thus wrist-worn pulse oximeters produces PPG signals which are highly contaminated by motion artifacts during any kind of physical activity. Besides the physical movements other motion artifacts are mainly the acceptance of ambient light leaking between the surfaces of the skin and sensor. Change in blood flow is also a major motion artifact. Frequency of noise signal lies mostly within the frequency range of PPG signals which in practical becomes difficult to denoise with conventional filtering techniques. A reliable heart rate estimation is usually done by first performing a series of preprocessing steps to denoise the signal and then followed by estimating the heart rate from the power spectral density [4]. Adaptive noise cancellation in a widely used technique for estimating heart rate from PPG signals which are highly motion corrupted [5]. For its ability of persistent processing and faster response time, adaptive noise cancellation holds a great advantage in noise removal technique. But selection of the proper reference noise is what holds its back. Obtaining correct real time reference noise can be difficult task. Synthetic noise application have been proposed [6] but nothing can overcome the authenticity of using real time reference noise. Analysis were done on contaminated PPG signals by using single noise reference signal, horizontal and vertical motion. The idea of applying pre-defined RNS has also been applied, but a pre-defined RNS cannot be applied for all the time windows of the PPG signal since motion artifacts in all time windows are not same [7]. The idea of applying a number of real time RNSs could overcome this problem rather than using a single one or a predefined one. We have implemented this theory and later compared every output from the adaptive filter to get the best possible estimation of the heart rate.

1.1 Background

People have been learning human body for centuries. One of the main reason behind that is to keep a human body healthy as long it has life. They have also came up with the fact that human body possess vital signs, which are in fact indicators of a person's essential body functions. Indicators contain mainly four vital signs; heart rate, blood pressure, respiratory rate and body temperature. We have been used to household thermometer used to measure body temperature and also commonly seen devices to measure blood pressure. Whereas heart rate is mainly measured in clinics and hospitals through conventional methods using electrocardiogram, ECG from large stationary machines. Analysis of heart rate helps in diagnosis and detection of coronary diseases. Measuring heart rate has a long tradition in medicine as a non-invasive indicator of illness [8]. Technological advancement led to much better devices with robust algorithm most of which were designed to be handy in hospitals These methods were analyzed with time and frequency domain, which measure the average magnitude of the R-R interval fluctuations around its mean value over a period of time. Later on research was done on methods based on chaos theory and nonlinear system. This interest were based on observation suggesting cardiovascular regulation interact with each other in nonlinear way. Then as PPG started developing it could be determined that PPG consisted of more vital information than ECG which is elaborately described in section 2.2. PPG have proved to be handier to obtain as less tools are needed to extract data. Thus the trends in developing more efficient systems in monitoring heart rate shifted towards the use of PPG signal over ECG. Later on various methods of obtaining heart rate have been discussed on section 1.3. Literature review talks about few of the most efficient methods of obtaining heart rate in the past years. Now we have reached the time of developing algorithms which are able to filter out the most contaminated of signals and give a heart rate estimation with least error. The usual heart rate among adults ranges between 60-100 beats per minute. And researches have proved that heart rate varies with body fitness. The person who is more fit is supposed to have a lower heart rate. Rise in heart rate above the normal range in known as tachycardia and the opposite case is named as bradycardia [9]. With the rise of mobile health monitoring devices, a real time monitoring of cardiac performance is increasingly being used outside medical settings. Now a days PPG is commonly used in measuring heart rate [10]. The general principle of PPG is that the fluctuation in the light absorption mode due to change in blood flow in the micro vascular vessel. This can be detected by a photodiode. This technology is accepted and widely used nowadays to measure vital indicators of our body. As the long term heart rate monitoring is very much in demand, so among the commonly used body parts to take PPG reading, wrist is the most ideal site for long term measurement in everyday life. Wearing it in other commonly used body parts which includes earlobes and fingertips did not seem comfortable for long term measurements. So embedding PPG sensors into our watch or a wristband seemed most natural for long term purposes. Numerous algorithm has been proposed to eliminate noise and all sorts of motion artifacts. Few have even implemented in commercially available smart devices to measure heart rate. More have been discussed on section 1.3 about few methods and their drawbacks, limitations in estimating heart rate and what can overcome the limitations of their methods.

1.2 Motivation

Cardiac activity always has great importance among all vital signs to monitor. It is possible to ensure the safety if track of heart rate is available. The number of beats per minute indicates the behavior of the heart. Rapid change in heart rates can be a sign of cardiac disease. Monitoring heart rate and activity is typically done by electrocardiogram method. Signals generate caused by electric activity in the cardiac tissue by connecting electrodes to the body. This is professional diagnostic method and by connecting maximum ten electrodes to the chest and limbs it is done. ECG signals provide information about the many components such as P,Q,R,S,T wave of one heartbeat in details. Now-a-days heart rate measurement from Photoplethysmogram (PPG) has been started. Though PPG signals generally used to measure blood oxygen saturation, but it can also provide cardiac information. With this technology, heart-rate monitors can be integrated in wearable devices. This is not possible in case of ECG.

The most challenging part is to measure the heart rate from PPG signals as they are corrupted by motion artifacts. In case of sleep studies, using optical devices is not a big problem, but it becomes difficult if the devices worn during exercise. The sensitivity of the signal decreases because of the motion between sensor and skin. We can minimize the impact by making the device attachment to the body more tightly, but not completely. After doing a long research most of the cases we found that heart rate estimation from ECG signals gave better result than PPG. Now people are giving more effort to get the more accurate or almost same result from PPG signals. We are living in a world where we are surrounded by too many blessings of technologies. Medical science has been advanced a lot and they are still working to make people life better. So, by assuming the estimated heart rate from ECG signals as ground truth we try to develop a method to estimate heart rate from PPG signals. Though it is quite challenging, we tried our best. If any method can be able to give most satisfactory results, it would be great help to mankind. Still today people don't give proper attention regarding this matter. The fact that motivated us a lot that is if device can be made that will estimate almost accurate heart rate with motion artifacts will decrease the rate of heart problem and it will make people more conscious about their health.

1.3 Literature Review

Biomedical technologies has increased rapidly in the recent years for more effective treatments and accurate diagnosis. In order to extract medically reliable data, medical monitoring devices should be optimized. There are various algorithm available to reduce motion artifacts from PPG signals. Many have been implemented in commercially available devices. A technique independent component analysis ICA on the basis of frequency domain proposed by Krishnan [11]. However his theory does not hold as the assumption in ICA, uncorrelation in not suited in motion corrupted PPG signal. Later in 2012 a heuristic algorithm of estimation heart rate from motion artifact corrupted PPG signal was proposed based on linear filtering and frequency domain analysis [12]. Previously more works have been done based on kalman filtering [13], wavelet denoising [14]. Most techniques based on linear filtering are not capable of denoising the signal efficiently. One of the most recent works involves heart rate estimation by empirical mode decomposition [15]. Another method of estimating heart rate was based on an adaptive and real time digital filtering technique [16].The heart rate here was determined using a zero crossing method. More methods include motion artifacts removal technique using electronic processing procedure [17] and time-frequency analysis [18]. In most of these works, the algorithms proposed have been developed to work against clinical challenges. Even the ones developed to fight motion artifact had very minor movements such as finger motion and walking. Very few have been working recently in high motion artifact and have developed an algorithm to denoise PPG to estimate heart rate. One of which is the TROIKA framework, where they proposed of signal decomposition for denoising, sparse signal reconstruction for high-resolution spectrum estimation with peak tracking verification [19]. The TROIKA framework greatly emphasizes on signal decomposition in order to remove motion artifacts put their system cannot remove all significantly important motion artifacts. Many of the algorithm proposed are transform based methods which are impractical to implement by hardware devices for real time application. The linear filtering methods are at times do not have the ability to denoise the signal efficiently. An ideal PPG signal in a quasi-periodic pulse, which have peaks, which is a poorly modeled with a pure sinusoid. Thus it is an underlying assumption in spectral estimation. Reducing motion artifacts by using a series of matched filters have also been practiced to exclude abnormal pulse shapes. The clean signal is then performed spectral estimation to obtain average heart rate from PPG data. Methods of obtaining frequency components using short-time Fourier transformation has proved to be robust just because data were obtained in small windows. Therefore the methods is not susceptible to a short part which is heavily contaminated by motion artifacts. A reliable heart rate estimation is usually done by first performing a series of preprocessing steps to denoise the signal and then followed by estimating the heart rate from the power spectral density [19]. Our work is mainly based on adaptive filtering from different noise channel and then evaluating each output by performing periodogram. Next peak tracking came into play from which heart rate was estimated.

1.4 Brief Summary of the Work

This thesis work is a proposed algorithm for estimating heart rate from a severely contaminated PPG signal with the application of adaptive filtering from multiple reference noise signals. First we have collected a reliable dataset from the work of TROIKA which was made open source for the Signal Processing Cup and for personal researches. So it was a reliable dataset which can be cited. It contained data set of 12 subjects who were being ran on treadmill at different speed for a specific time duration. The PPG signals were recorded from wrist by two pulse oximeters with green LEDs. The acceleration signal was also recorded from wrist by a three-axis accelerometer. Both the pulse oximeter and the accelerometer were embedded in a wristband, which was comfortably worn. The ECG signal was recorded simultaneously from the chest using wet ECG sensors. ECG was recorded to calculate actual heart rate which was later used to calculate error in our method. The basic concept was to use the three axis accelerometer data along with difference of the two channel PPG signal, which is also considered to be a noise signal as four set of reference noise signal. PPG was cleaned by adaptive filtering using the above mentioned four set of reference noise signals. A different set of PPG signal was collected with respect to each reference noise. All the set were windowed as required for comparing results. Heart rate was calculated from every window. We had four different heart rate for every window which was compared with each other also with the previous estimate to get an estimate in a systematic way. A peak verification technique was applied to estimate the heart rate. It can be concluded that the system can detect heart rate from any kind of physical activity. All the heart rate estimation were recorded and compared with the ground truth heart rate given from the ECG data.

Chapter 2 | Photoplethysmography (PPG)

2.1 History of Oximetry and Pulse Oximetry

Photoplethysmography (PPG), which is also known as pulse oximetry in general, is a noninvasive system to observe the blood oxygen saturation (SO_2) of a person. Though its reading of SpO_2 (peripheral oxygen saturation) is not always identical to the more desirable reading of SaO_2 (arterial oxygen saturation) from arterial blood gas analysis, the two are correlated well enough that the safe, convenient, noninvasive, inexpensive pulse oximetry method is valuable for measuring oxygen saturation in clinical use.

2.2 Oximetry

The measurement of oxygen saturation percentage of haemoglobin in blood is known as oximetry. Haemoglobin is a protein substance found in the red blood cells (RBCs) which transports oxygen from the lungs to all the living tissues of the body [20]. Light is transmitted through living tissues and depending on the concentration of oxygenated haemoglobin (HbO2) and deoxygenated haemoglobin (Hb), a transmission signal is sensed which is then used to calculate the percentage of oxygen in blood [21].

Figure 1 Portable pulse oximeter with PPG

2.2.1 Working Principles

A small sensory equipment is attached to a thin part of a test subject's body, most commonly a fingertip or an earlobe in case of an adult; across a foot in case of an infant. The device primarily emits two wavelengths of infrared signals (660nm and 940nm) through the body towards a photo detector on the other end. This type of PPG is known as the transmissive type [22].

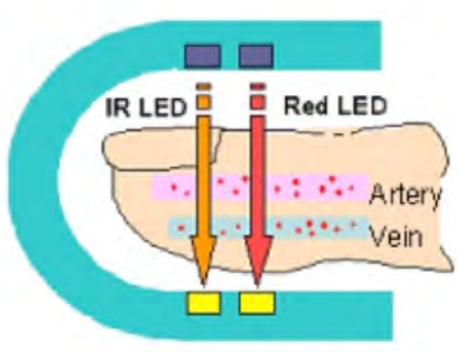


Figure 2 Transmissive pulse oximeter

Another type of PPG is known as the reflective type. In this case, the signals are sent from one side and the reflected waves are sensed on the same side.

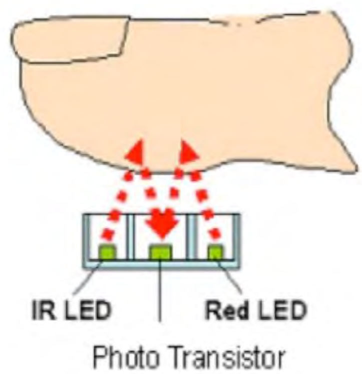


Figure 3 Reflective pulse oximeter

2.2.2 Estimation of Oxygen Saturation

Both the incident light signals pass through the patient's tissues and arterial blood supply. Oxygenated blood has a tendency to absorb 660nm signal and deoxygenated blood absorbs 940nm wavelength signals. As a result of this, the photoreceptor will receive a differential signal.

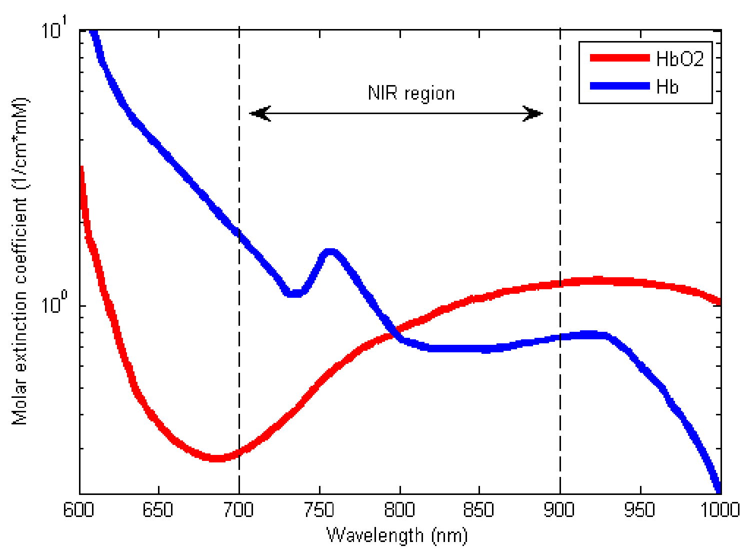
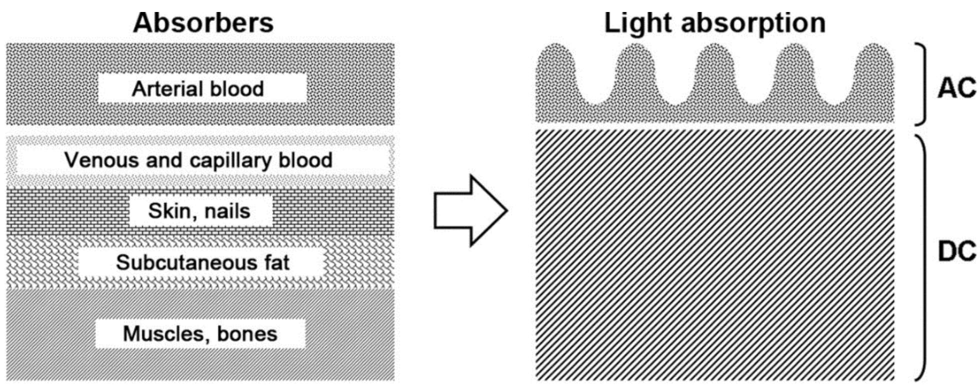


Figure 4 Absorption spectra of oxygenated haemoglobin (HbO2) and deoxygenated haemoglobin (Hb)

The differential signal has two main components: a pulsatile part (AC component) and a non-pulsatile part (DC component). The DC component is caused by the light absorbed by the skin, tissue, venous blood, bone, and nonpulsatile arterial blood. The AC component is caused by light absorption of pulsatile arterial blood [24].



$$SP_{O_2} = f(AC_{red}/DC_{red})/(AC_{infrared}/DC_{infrared})$$

Figure 5 DC and AC components of PPG caused by absorptions at various levels

The sensor determines the fluctuating absorbance of each signals, which allows it to calculate the absorbance caused by pulsating arterial blood ignoring noises created by other tissues of the body. Hence it can be used to calculate the test subject’s heart rate, saturation of oxygen and pulse waveform [23].

2.2.3 Heart Rate (HR) Calculation

The heart rate (HR) is calculated from the PPG signal using two common methods: peak to peak intervals and by observing the frequency content. The peak to peak intervals recognizes the peaks of the PPG signals and determines the interval between them. The later process, identifies the frequency of the signals by the use of Fourier Transform which generates a sharp spike that corresponds to the frequency of the heart rate.

2.3 Artifacts in PPG

The performance and accuracy of a pulse oximeter is determined by various factors that can hamper a PPG signal. The most detrimental artifacts that can corrupt a PPG signal such as that it cannot be used for medical applications are discussed in the following sub-chapters.

2.3.1 Motion Artifacts

The ambient light leaking from the gap between skin surfaces and sensor surfaces leads to motion artifacts along with the disruption in blood flow due to movements [25]. The noise created by movement of the sensory device due to waving, rubbing, seizures etc. of the patient's body during a treatment is also termed as motion artifact. As a result, the PPG signal is distorted in shape and leads to inefficient measurements which might cause unreliable treatment. Vertical or horizontal movement of the fingers induce low venous pressure that leads to motion artifact. This disturbance can affect the AC component of the PPG signal producing a lower oxygen saturation result [26]. Since the frequency band of the movements is similar to that of PPG, it is quite difficult to reduce the noise created by motion artifacts. Movement frequency is around 0.1Hz and above, while PPG signal is 0.5-4Hz [27].

2.3.2 Background Light Interference

The light from the operating room lamp or other sources can affect the pulse oximeter which will give rise to errors in the results. Other type of electromagnetic radiation such as from magnetic resonance imaging (MRI) can also cause interference. In addition to that, presence of intravascular dyes (methylene blue or indigo carmine) in blood can disrupt infrared and red wavelength absorption.

2.2.3 Anemia

The reduction of amount of red blood cells is defined as anemia. Anemia can affect the result of PPG by creating large error in oxygen saturation of the red blood cells [28]. Vasoconstriction, narrowing down of the blood vessels in order to reduce heat flow during the period of hypothermia can also be a problem in PPG measurements [29].

2.4 Applications and Limitations of PPG Sensors

In this section we are going to discuss about few application in PPG sensors. Assumptions made while observing and extracting data. How to handle PPG sensors are also discussed along with the basic limitations.

2.4.1 Sensor Placement

Until Ayogi's discovery of using pulse oximetry in finger, it has been commonly used by taking the measurement at earlobe [30]. In present days, finger is widely used to collect PPG signals through the sensors. In addition to fingers, PPG sensors now can also be placed in the chest, cheek and the forehead [31].

2.4.2 Basic Assumptions of Pulse Oximetry

Some assumptions are made during pulse oximetry in order to get a very accurate result [32]. Firstly, haemoglobin is present in the form of oxyhaemoglobin and deoxyhaemoglobin. Other forms of haemoglobin-carboxyhemoglobin and methemoglobin present in blood are neglected. Secondly, it is assumed that no other absorbers are present between the source of light and the photodetector. Lastly, it is assumed that all the blood that is pulsating is arterial blood. This assumption is incorrect due to the noise created by motion.

2.4.3 Applications of Pulse Oximetry

There is a wide application of pulse oximetry in the medical which covers anaesthesia, surgical operations, hypoxemia screening, and workouts and during transfers from operating room to the recovery room [33]. Pulse oximeters are commercially available as finger sensors at pharmacies and grocery stores for personal use which can be used to to observe oxygen saturation and heart rate (HR). These devices help to monitor heart rate (HR) and provide an idea to athletes to about the intensity of their workouts.

2.4.4 Drawbacks of Pulse Oximetry

Pulse oximetry is a very reliable and commonly used technology. However, this also have several limitations. The haemoglobin in blood is assumed to be composed of oxyhaemoglobin (HbO2) and deoxyhaemoglobin (Hb). However, other components of hemoglobin, including carboxyhemoglobin and methemoglobin neglected which gives rise to a small amount of error in some cases. The light sensitive photodetector can give misreading due to ambient light from the environment. This error can be corrected either by shielding the light sensitive part from ambient light or the ambient light can be measured and then minused from the raw signal.

correct signal= raw signal-ambient light signal

The pulsating PPG signal is a low signal in contrast to the DC signal. This can slightly be corrected by using an ADC with much higher resolution and brighter photodiodes. Reduced level of blood flow through the arteries can also cause the signal to be weak and hence the processing gets unreliable.

The following limitations can cause problems in pulse oximetry:

1. Other components of the body rather than only haemoglobin and deoxygenated haemoglobin absorbs the cause optical reflection.
2. Ambient light in the room can cause interference to the photodetector
3. The DC signal from the body has larger amplitude compared to the periodic PPG signal.
4. The signal might be weak due to less blood flowing through the blood vessels.
5. Noise caused by unwanted movements of the body.

Chapter 3 | Signal Processing Theory

3.1 Smoothing Filter

In signal processing smoothing any arbitrary signal or data set have in many cases have seem to reveal a sequential order. Once the pattern is revealed it gets easier for the observers to investigate the data or the respective signal. In smoothing, the data points of a signal are modified so that every points individually are reduced and points that are below than the adjacent points are increased. The abrupt fluctuation are presumably results due to noise. Thus leading to a smoother signal. Smoothing may lead to benefactor in a couple of ways in analyzing the data. One is being able to extract more information out of the signal. Another is providing analyses that are both robust and flexible for further research. There are several algorithms of smoothing a signal. A very popular technique is moving average method which is mostly used in statistical analysis. But the ones used in digital signal processing varies depending on the type, source, dimension, other major characteristics and of course, depends on what one wants to accomplish by filtering. Examples include butterworth filter, Kalman filter, low-pass filter, Savitzky-Golay smoothing filter and more.

3.1.1 Savitzky-Golay(SGolay) Smoothing Filter

SGolay filters derive directly from a particular formulation of the data smoothing problem in the time domain. SGolay filters were initially and are still used to render the relative widths and heights of spectral lines in noisy spectrometric data. Savitzky and Golay have proved that moving polynomial fit can be numerically handled in exactly the same way as a weighted moving average. This is only because the coefficients of the smoothing procedure are constant for all y values [38]. Thus SGolay smoothing is very handy to apply. Figure 7 shows a typical output of SGolay filtering. Figure 7 gives us an overview how the relevant data is extracted from the noisy signal. Figure 6 is the real time data of PPG data of test subject 1. Extensive use of SGolay filtering may also result in removal of relevant data in the original signal, so trial and error method is very much necessary to get best results from the provided data.

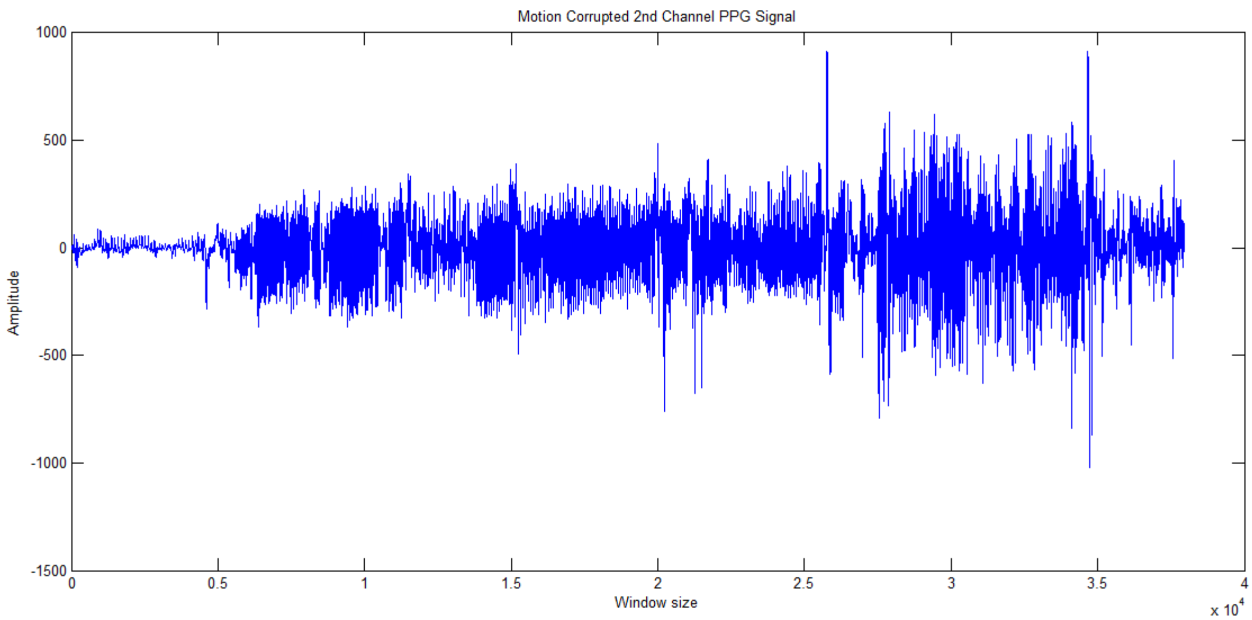


Figure 6 Motion Corrupted PPG Signal

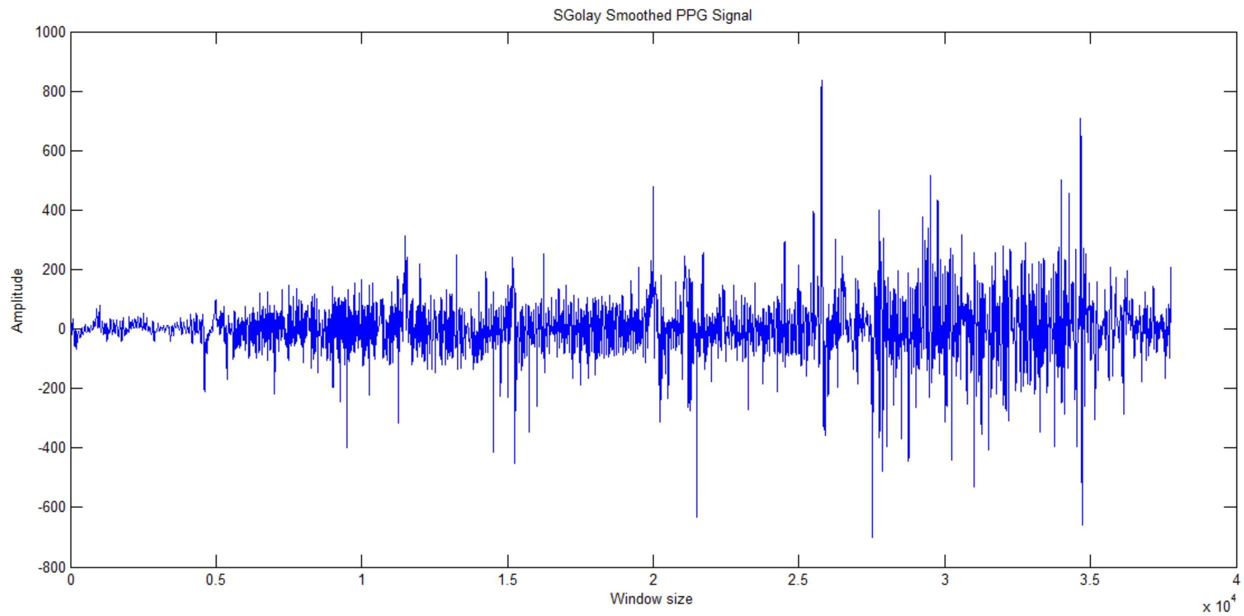


Figure 7 SGolay Smoothed PPG Signal

3.2 Adaptive Filter

Filter in signal processing is a general term used for a system related with noise removal. When working with random signals, often comes the time when the frequency behavior of the observing signal in not known. Overtime systems have evolved and came up with adaptive filtering. It is a closed loop system where it can change its parameters and is able to observe the variation in the signal overtime. In the following sections we are going to discuss more in depth about adaptive filtering and all the other different aspects of adaptive filtering related to this study.

3.2.1 Basic Adaptive Filter

Any real-time signal or data measuring technique includes some level of noise from different possible source as discussed earlier in section 2.3. Signal may also be introduced to noise by the signal processing system or in the sampling process. An adaptive filter can be described by four aspects as defined below:

- The signal being processed
- The structure that defines how the result signal of the filter is computed
- The parameters in the structure that changes with response to input output relation
- The algorithm that defines how the parameters are changed after each loop

An adaptive filter can be explained as a self-adjusting digital filter which alters its coefficient to put effort in error minimization. In general there are four major different types of adaptive filter configurations; adaptive system identification, adaptive linear prediction, adaptive noise cancellation and adaptive inverse system. All four systems have same general parts; an input x(n), a output signal y(n), a desired response d(n), an adaptive transfer function w(n) and an error function e(n). Figure 8 shows a simple block diagram of an adaptive filter system. The error function is simply a function of the difference of distance between the desired signal and the output of the adaptive filter. As it is a real-time self-adjusting system, it is sometimes expected to analyze the performance of a slowly changing signal. The error signal e(n) is calculated from the desired response d(n). As time progresses the output signal y(n) is hoped to get better and close to d(n). This model mostly describes a linear model. In our problem the input signal x(n) and desired signal d(n) changes with respect to time. Obviously the relation is not linear and the adaptive filter must need to change its parameter values to adapt the varying relationship. Such methods are defined as tracking. The configuration we worked with is the adaptive noise cancellation.

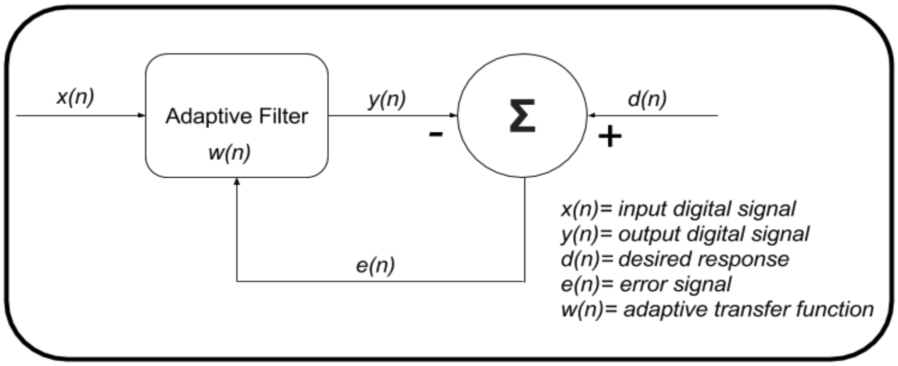


Figure 8 Basic Block Diagram of Adaptive Filter

Adaptive filter has been used over and over again in order to filter out noise from electrocardiogram, PPG any various other biomedical signals [34]. As the potential of digital signal processors are increasing, the usage of adaptive filter is becoming a common scene in mobile phones, other communication devices and health monitoring equipment to filter noise.

3.2.2 Least Mean Squares (LMS) Adaptive Filter

LMS is a type of adaptive filter whose main principle is to minimize mean square error which is the difference between the desired function and the actual signal. In produces filter coefficients which produces the least mean square error. The coefficients are estimated continuously. This means in the following way the desired output is computed by filtering the input with a weighted vector after which the error is calculated, the difference between the desired signal and the filter output. This process keeps on going and the weighted vector is updated in motive to minimize the error. Two parameters the length, or number of coefficients of the filter, and the step size. The step size being too small can significantly increase the time taken in finding the correct coefficients for convergence. Large values can even cause upset by making the filter unstable and be unable to converge on the proper coefficients. So step size need to be chosen wisely according to the size of data window.

3.2.3 Recursive Least Square (RLS) Adaptive Filter

Recursive Least Square is another class of adaptive filters which functions by minimizing the sum of error square. RLS algorithm input signals are considered to be deterministic, meaning there is no randomness. Whereas the LMS filter assumes its input signal to be stochastic or random. The advantage of RLS algorithms compared to others is that it has unbelievingly fast convergence. This is because it uses a constant known as the forgetting factor. This is a decaying value which makes the algorithm forget about the past vector information at a certain rate. This value is usually set close to 1 which makes the algorithm forget a certain portion of information to estimate its parameters. When set to 1 the system remembers every past values and uses all information available to estimate the coefficients.

3.2.4 Adaptive Noise Cancellation

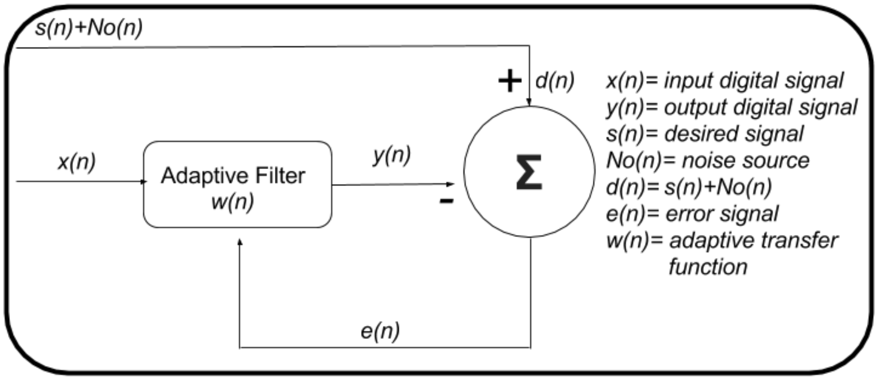


Figure 9 Basic Block Diagram of Adaptive Noise Cancellation

The ANC consists of two inputs, the primary noise input x(n) and a reference signal d(n), shown in figure 9 which is in fact consist of a signal s(n) corrupted by another noise No(n). The primary input is a mix of the signal from the source corrupted by noise (signal, s(n) + noise, No(n)). The reference input is either correlated with noise or the signal. If correlated with noise the output of the adaptive filter y(n) are going to be a close estimate of the primary input noise. By subtracting the noise estimate from the corrupted signal the system output of the ANC will hence be an estimate of the signal. Similarly if the reference signal is correlated with the signal source the system output of the adaptive noise canceller is going to be an estimate of the noise. An adaptive process updates the filter coefficient based on the algorithm that is being used [35]. The error signal e(n) should converge to signal s(n), but not converge to exact signal. In more simpler terms, the difference between the signal s(n) and error signal e(n) will always be greater than zero. Our aim is to minimize the difference between the two signals.

3.2.5 Reference Noise Cancellation

Reference noise cancellation is simply another term for adaptive noise cancellation. Every adaptive filters has got its own sets of noise depending on the source, method of communication and other aspects. Here we discuss about the reference noise we had to work. The reference noise we mainly focused on were the motion artifacts data collected from the recordings of 3-axis acceleration data. Accelerometers measure acceleration, often caused by motion. Accelerometers are electromechanical devices that sense either static or dynamic forces of acceleration. Static force is like the constant force of gravity pulling at our feet, while dynamic forces are vibrations and movements.

3.2.5.1 Motion on the wrist in x-axis

This is basically the accelerometer data of the x-axis. This records the acceleration of the subject on x-direction. We had done adaptive filtering with respect to four difference RNS separately so each data is necessary for the proposed method. Figure 10 represents x-axis data of subject 1.

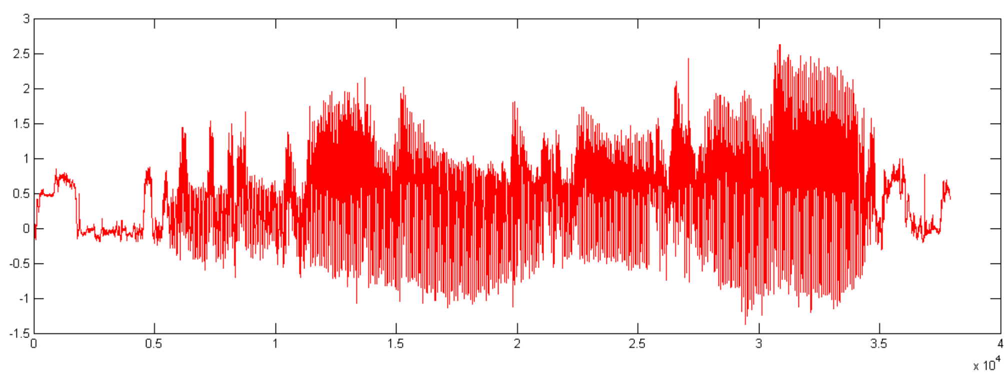


Figure 10 Accelerometer Data of x-axis

3.2.5.2 Motion on the wrist in y-axis

Similarly to the x-axis this part shows us a real time y-axis data from the accelerometer of test subject 1 shown in figure 11. This y-axis data is treated the same way as x-axis.

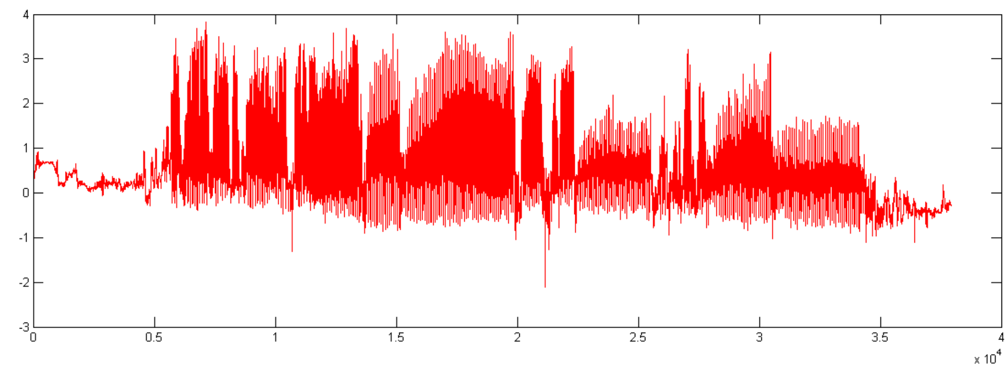


Figure 11 Accelerometer Data of y-axis

3.2.5.3 Motion on the wrist in z-axis

The acceleration occurred in the direction of z-axis shown in figure 12. This data is also similarly treated as the other two axis data. The result output of the adaptive filter is processed to the next step where power spectrum density takes place in order to compare the values with output of other adaptive filters.

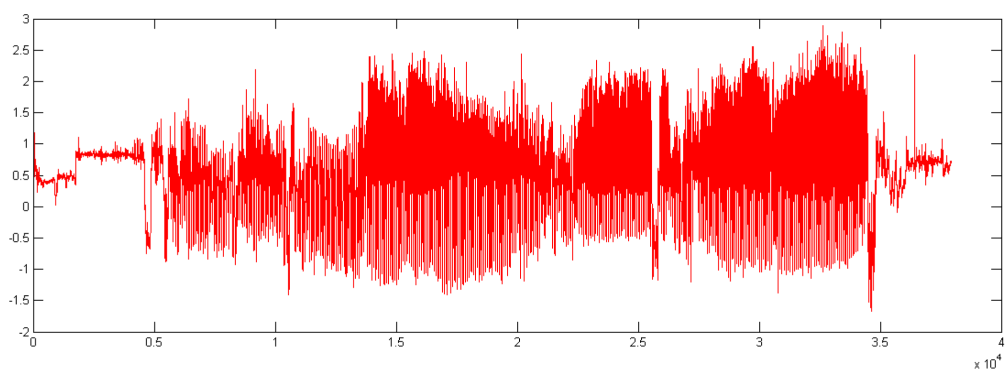


Figure 12 Accelerometer Data of z-axis

3.2.5.3 Difference between 2-channel PPG signals

The two channel PPG is supposed to carry almost similar vital information but due to tissue effect related artifacts and venous blood movement we have a difference in between the two PPG signals [36]. We used this as our fourth reference noise signal. This reference noise is similarly treated as other 3-axis motion noise in order to estimate peak.

3.3 Periodogram

A periodogram calculates the significance of different frequencies in time-series data to identify any intrinsic periodic signals. A periodogram is similar to the Fourier Transform, but is optimized for unevenly time-sampled data, and for different shapes in periodic signals.

3.3.1 Peak Detection

Power spectrum represents the energy distribution of a time series in the frequency domain. As Energy is a real-valued quantity, so the power spectrum has no phase information. Because time series may contain non-periodic or asynchronously-sampled periodic signal components, the power spectrum of a time series generally is a continuous function of frequency. A series of discrete frequency represents the continuous frequency, the value at a specific frequency bin is proportional to the frequency interval. To remove the dependence on the size of the frequency interval, normalize the power spectrum to produce the power spectral density (PSD), which is power spectrum divided by the size of frequency interval.

3.3.2 Parametric methods

These are based on parametric models of time series, such as autoregressive-moving average (ARMA) models, moving average (MA) models, and AR models. Parametric methods are known as model-based method also. To estimate the PSD of a time series with parametric methods, the model parameters of the time series need to be obtained first.

3.3.3 Nonparametric methods

These methods, which include the Periodogram method, Capon method, Welch method. These are based on the discrete Fourier transform. Obtaining the parameters of the time series before using these methods are not needed. For heart rate estimation, we compute the frequency spectrum of each of the cleaned PPG signals using a periodogram method. Periodogram is used to identify the dominant periods of a time series. It is useful to identify the dominant cyclical behavior in a series, especially when the cycles are not related to the commonly experienced monthly or quarterly seasonality. We performed nonparametric periodogram to our adaptive noise cancelled PPG data.

Chapter 4 | Proposal Method

The algorithm consisted of several steps of filtering to peak detection. The block diagram in figure gives a brief idea of the proposal method.

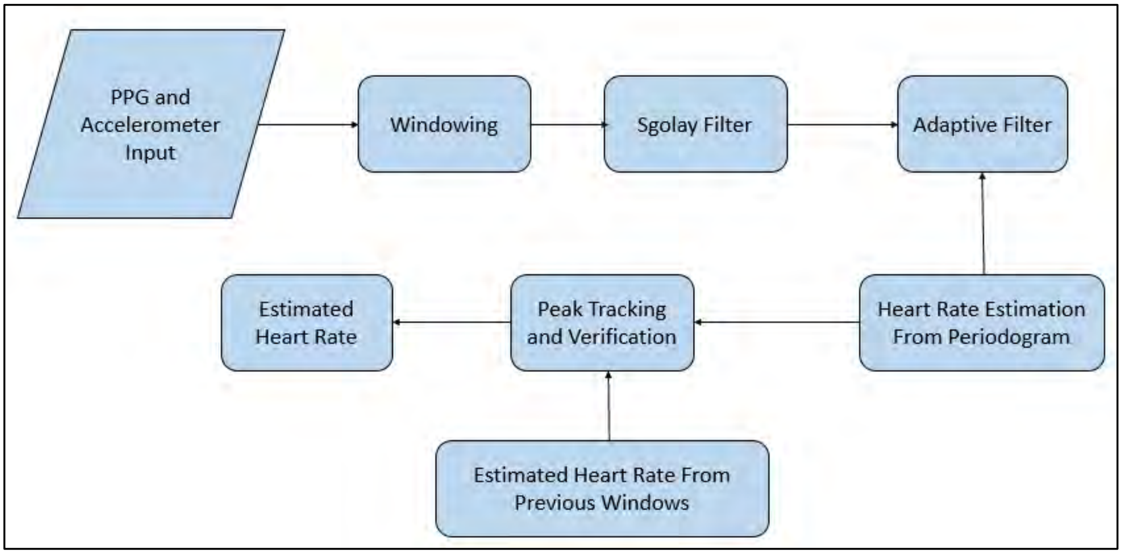


Figure 13 Block Diagram of Proposed Method

4.1 Windowing and Indexing

The model of a PPG signal can be modelled mathematically as

$$p_i(k)=h_i(k)+m_i(k)$$

where i and k are simply index of the sample and index of PPG signal respectively[37]. $p_i(k)$ is the PPG signal extracted from the sensor which is contaminated by motion artifact. $h_i(k)$ is the PPG signal which is free of motion artifacts and lastly $m_i(k)$ is the signal which defines the motion artifacts. Our goal is to properly define $h_i(k)$ from where we can estimate heart rate by using spectrum analysis and peak detection. As our ground truth is defined on 8-second time window and the successive time window overlaps the previous by 6 second. Thus the first BPM is for the first 8 second and the second BPM is from the 3rd to the 10th second. Thus there was increment of only 2 seconds. Therefore in order to estimate heart rate we need to represent the motion corrupted PPG data according to the ground truth. After analyzing the data we divided the PPG signal in window size, *n* and the increment, *l* due to the overlapping. After doing the math we came up with *n* =1000 and *l* =250. PPG signals were recorded for each subject for 5 minutes and when it was converted to digital signal it had index ranging from approximately 35000 to 40000. Each second represents

$$40000/(5*60)=133.33 \text{ units}$$

So an 8 second time window would represent

$$l = 133.33*8=1066.66 \text{ units}$$

And a 2 second time window would represent

$$n = 133.33*2=266.66 \text{ units}$$

As most of the total indexing of the PPG data were less than 40000 a base window size, *l* of 1000 was chosen and similarly increment window, *n* was chosen 250. Thus the motion artifact included PPG signal can be formulated according to the following equation

$$\begin{aligned} P_i^k &= [p_i(n_k)p_i(n_k+1)\ldots\ldots p(n_k+l-1)]^T \\ &= [p_i^k(0)p_i^k(1)\ldots\ldots p_i^k(l-1)] \end{aligned}$$

Where P_i^k represented the i^{th} channel of the 2-channel PPG data of k^{th} window. The value of k can be determined simply by deducting *l* from the length of PPG, then dividing the result with *n* and adding 1 to it. Similarly the motion acceleration data were treated as they were going to be used as reference noise signals. Acceleration data can be denoted as

$$\begin{aligned} a_j^k &= [a_j(n_k)a_j(n_k+1)\ldots\ldots a(n_k+l-1)]^T \\ &= [a_j^k(0)a_j^k(1)\ldots\ldots a_j^k(l-1)] \end{aligned}$$

The new term j here is nothing but simply the accelerometer data of the j-axis. As mentioned before we used 3-axis data to act as our reference noise signals. The aim of our thesis work is to estimate heart rate from each window of P_i^k by using their corresponding a_j^k as its reference noise.

4.2 Savitzky-Golay Smoothing under Time Domain

We have seen the advantages of Savitzky-Golay (SGolay) operation as smoothing technique in section 3.1.1. Now we perform it in a repetitive manner for better smoothing to all the data signal, PPG signals along with the 3-axis accelerometer data. As mentioned in section 3.1.1 excessive repetition can lead to loss of vital physiological data from the PPG signal. The recursive manner can be shown as

$$\mathbf{P_i^0 = SG\{p_i^0(0)p^0{}_i(1)....p_i^0(\mathit{l}\,-1)\}}$$
$$\mathbf{P_i^1 = SG\{p_i^0(\mathit{n}).....p^0{}_i(\mathit{l}\,-1)p_i^1(\mathit{l}\,-\,\mathit{n}).....p_i^1(\mathit{l}\,-1)\}}$$
.
.
$$\mathbf{p_i^k = SG\ \{[p_i^{k-1}(\mathit{n}).....p^{k-1}(\mathit{l}\,-1)p^k{}_i(\mathit{l}\,-\,\mathit{n}).....p_i^k(\mathit{l}\,-1)]\}}$$

SG represents SGolay filtering on the given data signal. SGolay filtering is performed for every k^{th} window. We have given raw data of PPG signal in the first window. From the successive window raw data of next 2 seconds is added with the previous data of 6 seconds keeping the window size as mentioned before of 8 seconds.

This process is done in a recursive manner which means every P_i^k signal is filtered repetitively until a satisfactory data is processed keeping the vital information within the signal. This method of filtering provides us with inflection points with higher order moments. Normal digital finite impulse response, FIR filters is unable to do. This gives SGolay filtering an upper hand over digital FIR filters [38].

Moreover SGolay filtering also able to hold local maxima and minima by performing least square polynomial fit across each point. This way original shape of the signal is preserved along with the height of waveform peaks in the process of removing noise up to a certain level. Thus smoothing is done and a satisfactory data to be processed is extracted. The accelerometer data a_j^k is also treated in the same way to receive a smoothed a_j^k for adaptive filtering. Now we have achieved smoothed data of the 2-channel PPG signal and also for the 3-axis accelerometer data.

4.3 Adaptive Noise Cancellation on Smoothed PPG Signal

Recursive Least Square, RLS based adaptive filtering have been discussed elaborately earlier in section 3.2.4 and 3.2.5. Now we are going to perform RLS based adaptive noise cancellation to our SGolay smoothed PPG data to reducing motion artifacts. Before that we have to figure out our fourth reference noise signal which as mentioned in section 3.2.5.3 is the noise named as the difference between the 2-channel PPG signals. Even though the PPG signals being collected from the same patient the two PPG signals have shown a significant difference between them due to body tissue related artifacts and abrupt arterial blood movements. This might also occur due to the signal strength being strong of one PPG signal more than the other. So a scaling parameter, *b* is multiplied with the one of the signal so that the intensity of both PPG signal somewhat matches with one another. The value of *b* is determined such that if,

$$\mathbf{P_2^k < p_1^k \text{, then } \boldsymbol{b} > 1 \text{ else if}}$$
$$\mathbf{P_2^k > p_1^k \text{, then } \boldsymbol{b} < 1}$$

The value of *b* was set to be 1.05 for our research depending on the intensity of the two PPG sources. Then finally our 4^{th} reference noise signal, d^k that is the difference between the two PPG signals was calculated which can be expressed by the following formulae,

$$d^k = p_1^k - b * P_2^k$$

Next the mean from all reference noise signal data is calculated and deducted from the smoothed noise signal. This ensures the DC component from all the noise signal is neglected before adaptive filtering is computed. Now we have our all desired reference noise signals and ready to go through adaptive noise cancellation.

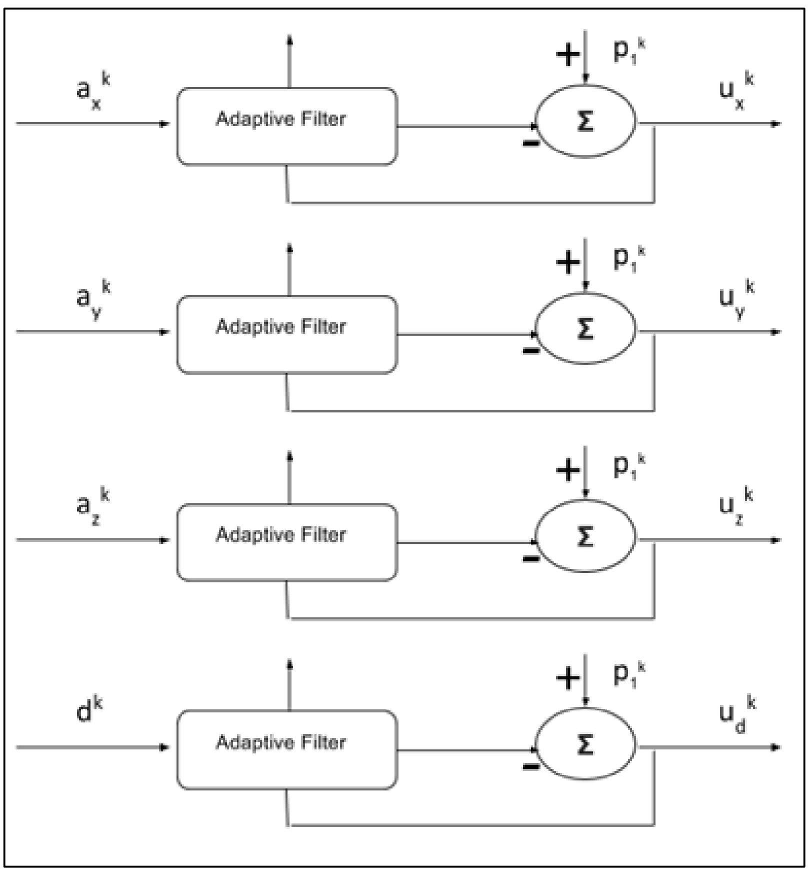


Figure 14 Block Diagram of Multiple RNS Motion Reduction Method

Adaptive noise cancellation was performed as shown in the block diagram in figure 14. Four blocks of adaptive filtering for each of the RNS. Each estimated motion artifact signal is now deducted from the SGolay smoothed PPG signal. We now have four separate cleaned PPG signal respect to their reference noise, u_x^k, u_y^k, u_z^k and u_d^k. Every k^{th} window of all the reference noise has got its own different version of cleaned PPG signal.

4.4 Detection of peak

Heart rate estimation from PPG is solely based on determining the peak from the frequency component of the PPG signal. The frequency component of the peak is taken into account for all the k number of windows. Frequency spectrum of all the adaptive noise cleaned PPG signal in determined by performing non parametric periodogram as earlier mentioned in section 3.3.3 because our data was in cycles not related to the commonly experienced. The usual heart rate of a human body whether healthy or ill ranges from 60 BPM to 240 BPM. From that we can compute the corresponding frequencies ranges from 1Hz to 4Hz. So before proceeding further, frequency component higher than 4Hz and also frequency components lower than 1Hz are omitted. Thus it gets easier for the system to determine the natural occurring peaks. The peaks from the periodogram of the desired range are taken into account. The one with the greatest magnitude is figured out and the index is saved which is probably the location of current heart rate. Just to mention we have four different heart rate respect to four different RNS of the exact same window. Not all are chosen but one. But before choosing the appropriate peak we performed heart rate estimation with respect to all four reference noise signal. The ground truth against estimated heart rate of respective RNS graphs are plotted below.

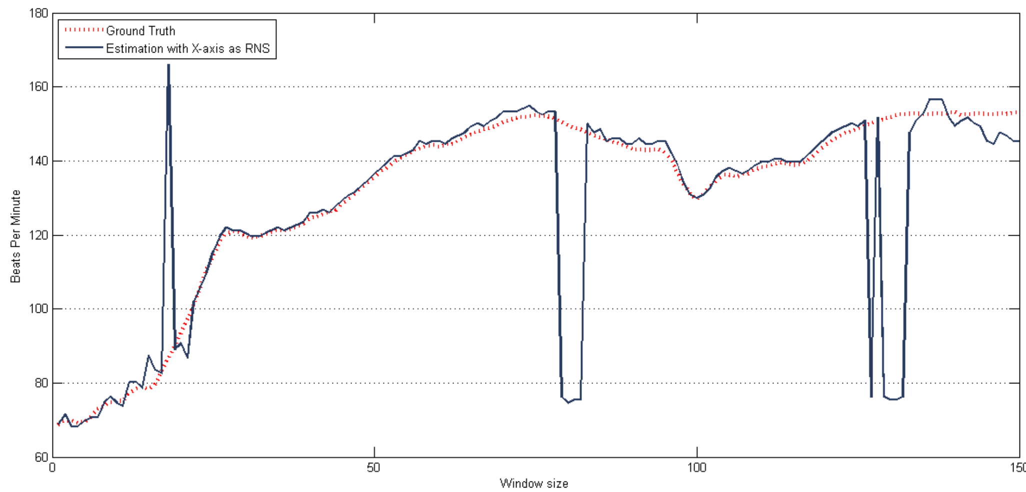


Figure 15 Estimation Result on Dataset 12 with x-axis Training Data as RNS

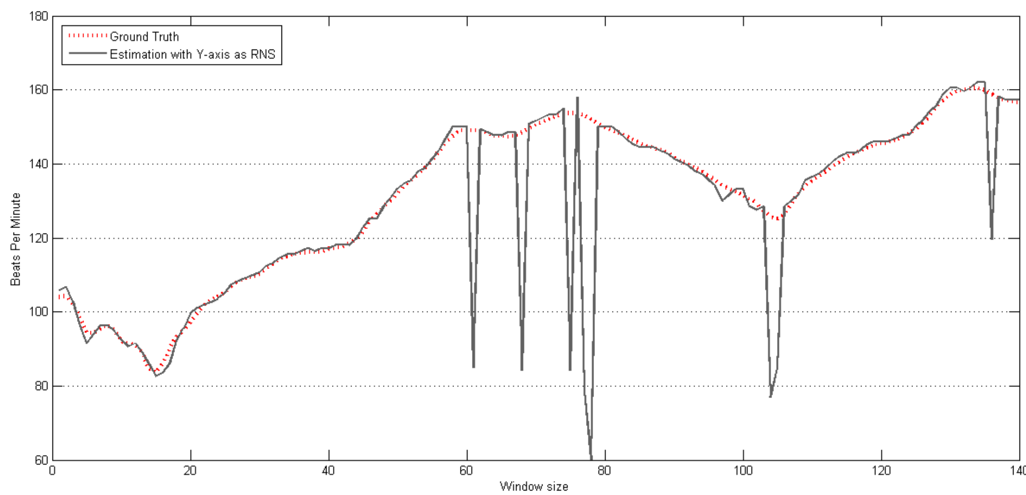


Figure 16 Estimation Result on Dataset 4 with y-axis Training Data as RNS

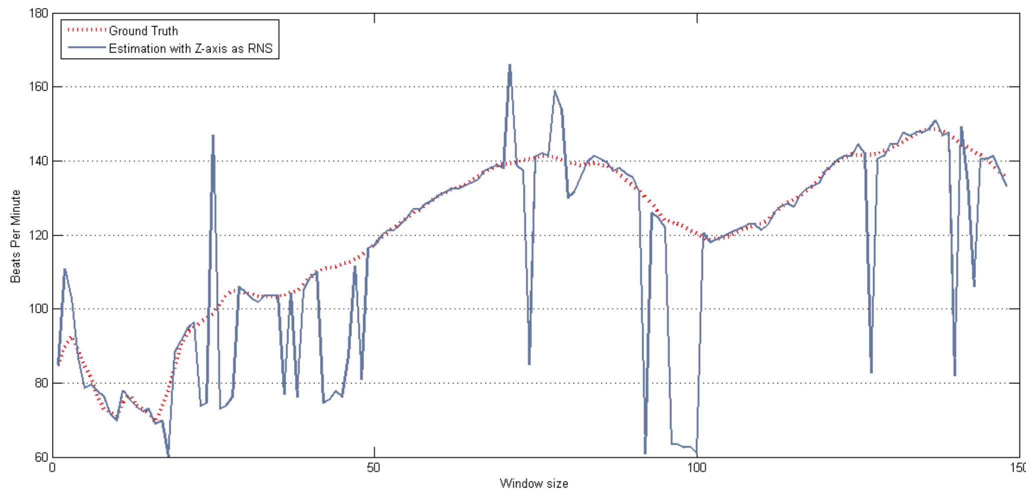


Figure 17 Estimation Result on Dataset 02 with x-axis Training Data as RNS

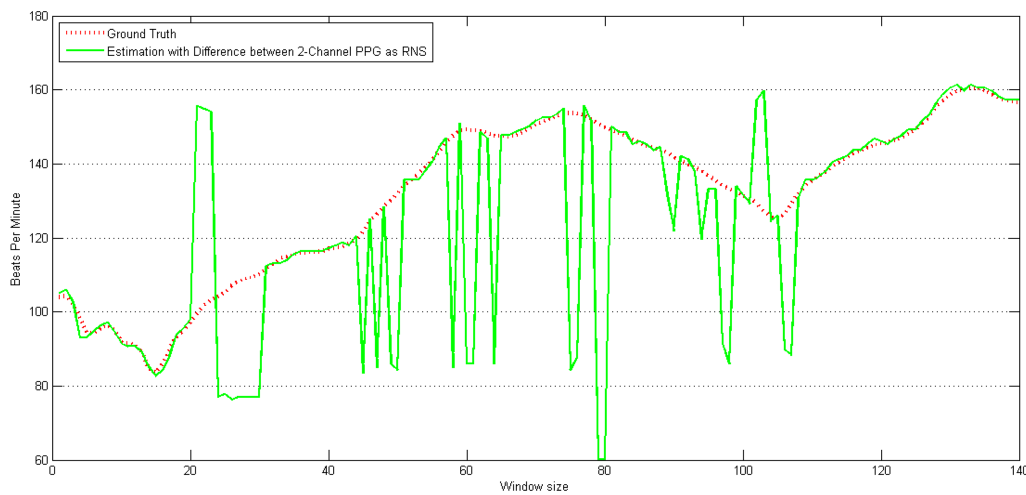


Figure 18 Estimation Result on Dataset 12 with difference between 2-channel PPG Data as RNS

This is after which peak tracking and verification is activated. How the location of the peak is chosen is discussed in the following section.

4.5 Peak Tracking, Selection and Verification

One of the most essential part where the correct peak in chosen over a pool of four available peaks. It is important to choose the appropriate peak in order to estimate the best possible heart rate. In order to ensure we get the best heart rate estimation peak tracking and peak verification, two orderly algorithm is applied which is further discussed below.

4.5.1 Peak Selection of the First Window

Peak estimation of the initial window was treated differently than the other following windows. As no other previous data or measurement was available estimation made solely depends on the first window. It was also mentioned that every subjects were rested for the first 30 seconds which leads to the fact that there were way less motion artifacts than the windows that followed afterwards.

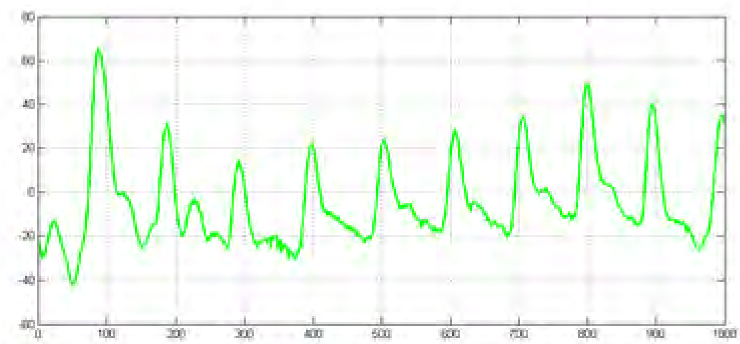


Figure 19 PPG before exercise

So the first window had an advantage over the others as shown in figure 19 where the PPG data is almost alike an ideal clean PPG signal. Heart rate for the initial window can be calculated by conventional method. Whereas in figure 20 it can be seen how corrupted the PPG signal is from motion artifacts. It cannot be even recognized as PPG signal. From this we can conclude that there will be hardly any change in the adaptive noise cancellation applied PPG signal with the raw PPG signal of the initial window. So heart rate was estimated from the data of the 2 raw PPG signals.

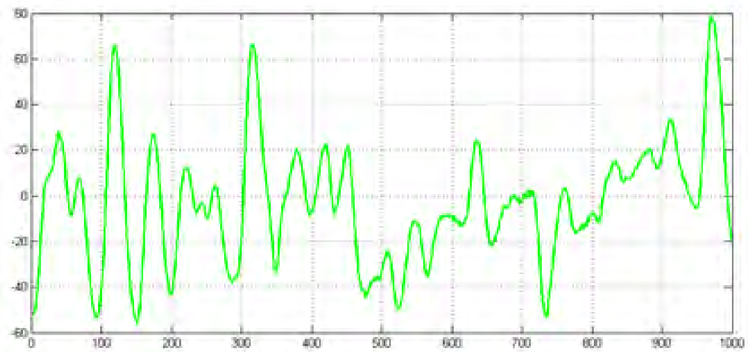


Figure 20 PPG during exercise

4.5.2 Peak Tracking

After the multiple adaptive noise cancellation, peak tracking is another fundamental part of the thesis project which needs to be highlighted. From the second window onwards the peak tracking program is activated to estimate best possible heart rate. As already mentioned before that for each windows we have four estimated heart rate any one of them needs to get selected. What previous study have shown us that heart rate as an indicator of the human body does not change rapidly within a small given time. Moreover in this case, there percentage of overlapping of previous data on the current data equals to almost 75%. Thus there is hardly any possibility of large change of heart rate in the successive window from the previous. The difference in heart rate is calculated of the current four estimates with the heart rate estimate from the previous window. As large change is unacceptable according to the phenomenon, so we have to select the heart rate which has the least difference with the one of the previous window.

4.5.3 Heart Rate Verification

Small negligence in peak tracking method related with motion artifacts can lead to large errors in heart rate estimation. So it is important to verify the estimated heart rate regularly [19]. A method of adding a fixed value if estimated heart rate exceeded by a significant amount from the previous one was proposed [39]. The TROIKA structure proposed a verification method based on a trend in heart rate [19]. In our structure we also applied an organized verification method. It starts right after the power of motion artifacts increasing. It progresses by recording the differences of the current window block with the last five blocks. If differences exceeds a threshold then the next step in the method is activated. The next step takes the three highest peaks from the periodogram of the current window and saves their locations respectively. The corresponding power of the top three peaks are recorded from the periodogram. Then the noise power is calculated by forming a signal by the combination of accelerometer data. The absolute square sum is calculated by taking the magnitudes of the 3-axis accelerometer of the previously saved location. Then conventional signal to noise ratio SNR is calculated. The heart rate of the location who has the highest SNR is chosen. If the SNR wise chosen heart rate has less difference with the 5 previous estimated heart rate, it is replaced with the current estimate but if the difference is more, than the current estimated heart rate from the adaptive noise cancellation is held.

Chapter 5 | Results and Discussion

5.1 Results and Performance

Results were mainly judged on performance basis. The interpretation of heart rate according to the proposed method was evaluated on few criterions. We had the window wise ground truth beats per minute, BPM of all the subjects. This ground truth BPM collected from respective patient's ECG signal were used to rate the performance of our algorithm. The first error was calculated based on the following formula

$$Error = 1/k \sum_{i=1}^{k} |\mathrm{BPMest(i)} - \mathrm{BPMo(i)}|$$

Where BPMest(i) is the estimated BPM of the i^{th} window and similarly BPMo(i) is the ground truth BPM. The sum of the difference taken from all windows are calculated and the average is computed by dividing the sum with all k number of windows. This gives us the absolute average error. This is done for every subjects and the results are shown in table 1. Percentage error was also calculated to give better explanation in terms of accuracy of the algorithm. The equation for calculating percentage error is

$$\%\, Error = 1/k \sum_{i=1}^{k} \frac{|\mathrm{BPMest(i)} - \mathrm{BPMo(i)}|}{\mathrm{BPMo(i)}}$$

This equation simply gives us an idea of the percentage error from the ground truth BPM. Percentage error for all the patient's heart rate are also given in the table 1.

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	P11	P12	Avg
Error	2.44	2.23	0.75	0.94	0.68	6.25	0.87	0.62	0.74	3.22	1.16	0.89	1.73
%Error	1.90	1.87	1.66	1.82	1.49	2.25	1.26	1.62	1.59	2.93	1.15	1.99	1.79

Table 1 Absolute error and absolute percentage error of all 12 subjects

It can be concluded that the average absolute error is about 1.73 BPM and the percentage error is around 1.79%. The average error values gives us the idea that the algorithm produced fair results in terms of BPM. In figure21 and 22 scatter plot of BPMest against BPMo is plotted to give us an idea how the algorithm performed. This briefly illustrates that how far were the estimated heart rate from the ground truth heart rate. The respective scatter plot is of the 2nd patient and 6th patient.

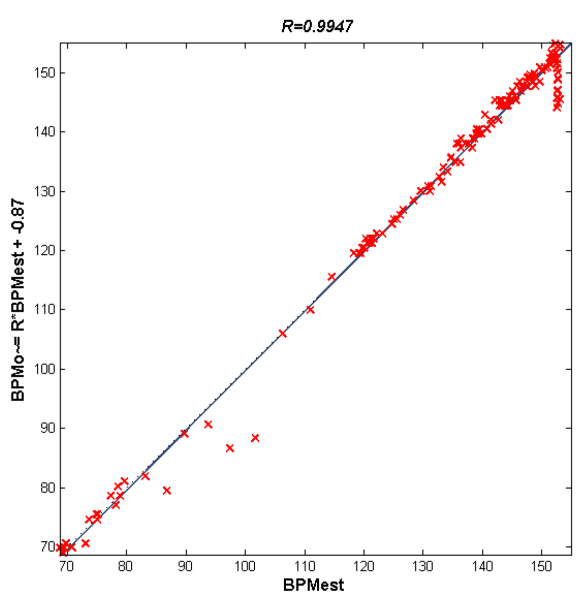


Figure 21 Scatter Plot of 6th subject

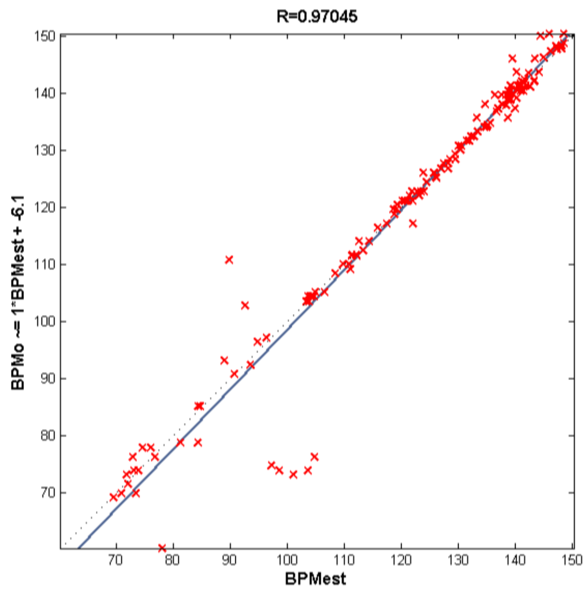


Figure 22 Scatter Plot of 2nd subject

The scatter plot defines a lot about the efficacy of the algorithm. In the estimated heart rate of patient 2, there are few points very far from the ground truth, as the system progresses it can estimate which have very high accuracy. On the other hand heart rate estimation of patient 6 had better results compared to patient 2. Almost all the result were similar to that of patient 6. Scatter plot of estimated heart rate of all the subjects are given at the end.

Two of the best continuous heart rate monitoring are shown below. In this graph the estimated heart rate is plotted against the ground truth heart rate. Patient 4 dataset gave the best estimated heart rate with a percentage error within a very acceptable range.

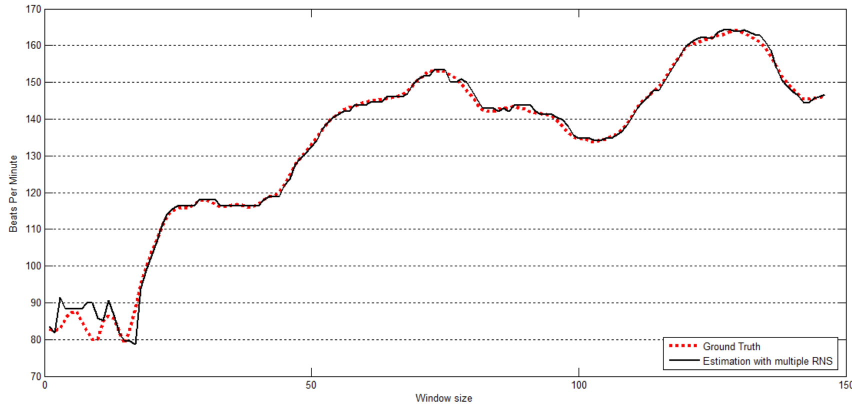


Figure 23 Result on 4th patient dataset

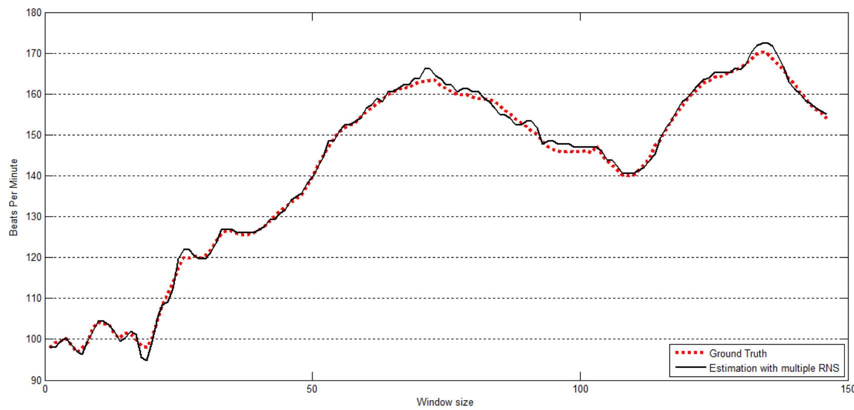


Figure 24 Result on 12th patient dataset

5.2 Data Description

PPG signal and corresponding accelerometer data along with the ground truth heart rate were collected from the archive of Signal Processing Cup, which originated from the experiment of TROIKA [19]. A collection of 12 data set of 12 different subjects where each of them had 6 rows. The first row is a simultaneous recording of ECG, which is recorded from the chest of each subject. The second row and the third row are two channels of PPG, which are recorded from the wrist of each subject. The last three rows are simultaneous recordings of acceleration data (in x-, y-, and z-axis). Each data set had another corresponding data set where the ground truth BPM were recorded. During recording each subject were rested for the first 30 seconds and then they started running with speed varying from 0 to 15km/h.

5.3 Parameters

We used few built in function in Matlab which required its parameters to be set up. The RLS adaptive filter had its own few parameters. The forgetting factor as mentioned section 3.2.3 was set close to 1 so it remembers most of the previous result. Its filter order was selected to be 32. Experiment was also conducted with filter order of 64. The window length was chosen to be 1000 with an increment of 250. And lastly to neglect the unnecessary frequency component after periodogram, 300 frequency spots were chosen with frequency range of 0 to 4 Hertz.

5.4 Discussion

Though the PPG data we had was extremely motion corrupted, all the data type was very similar that is running on a treadmill. The experiment would have been more flexible if we had various types of motion corrupted data like while playing football, boxing or swimming. The concept of adaptive filter was clear as it has been put into application before.

Chapter 6 | Conclusion

In this thesis project we formed a framework for estimating heart rate for 12 subjects from their corresponding PPG signals recorded from wrist by two pulse oximeters. Given that PPG signal is a very low cost technique to achieve vital physiological signals. The algorithm consisted 3 crucial parts in estimating the best possible heart rate. First comes the implement of multiple reference noise signal in adaptive noise cancellation which gives clean PPG signal of four different versions. The next key part is the peak tracking system and lastly the methodical verification system. The results of the estimated heart rate falls in the acceptable range given it had suffered very high motion artifacts. The experimental result shows the system can handle PPG signals to estimate heart rate even if they are severely contaminated with noise artifacts. The flexibility range is extremely wide and proper implementation of the algorithm in hardware can produce brilliant results which can take wearable heart rate monitoring system to greater heights. The system can be developed further to extract other vital information from PPG signal and thus add more value to the overall system.

Illustrated Results

Results of estimated heart rate and their corresponding Scatter plot are illustrated below

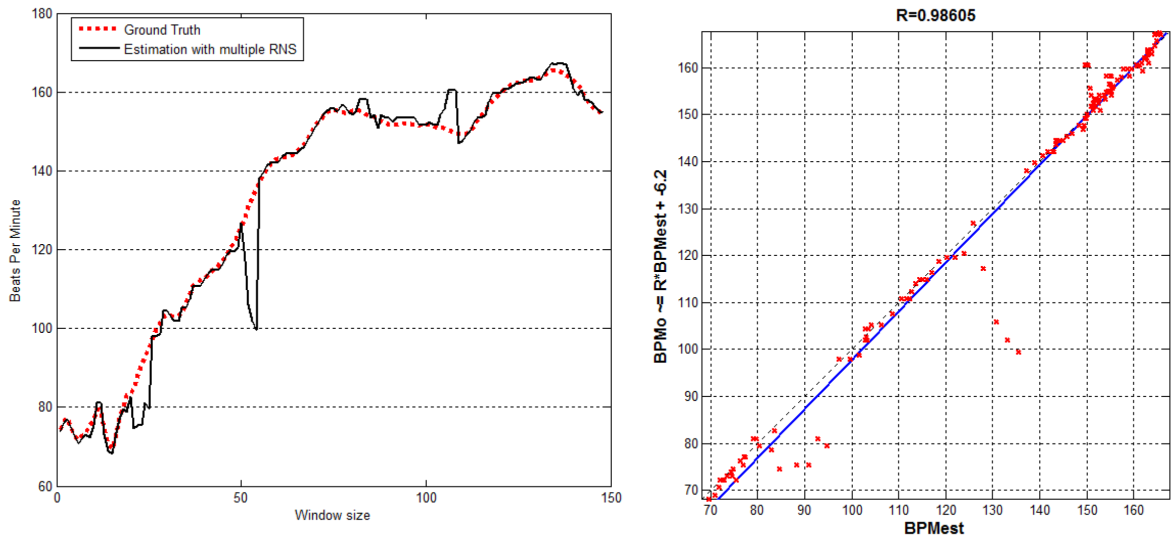


Figure 25 Estimation result on test subject 1 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

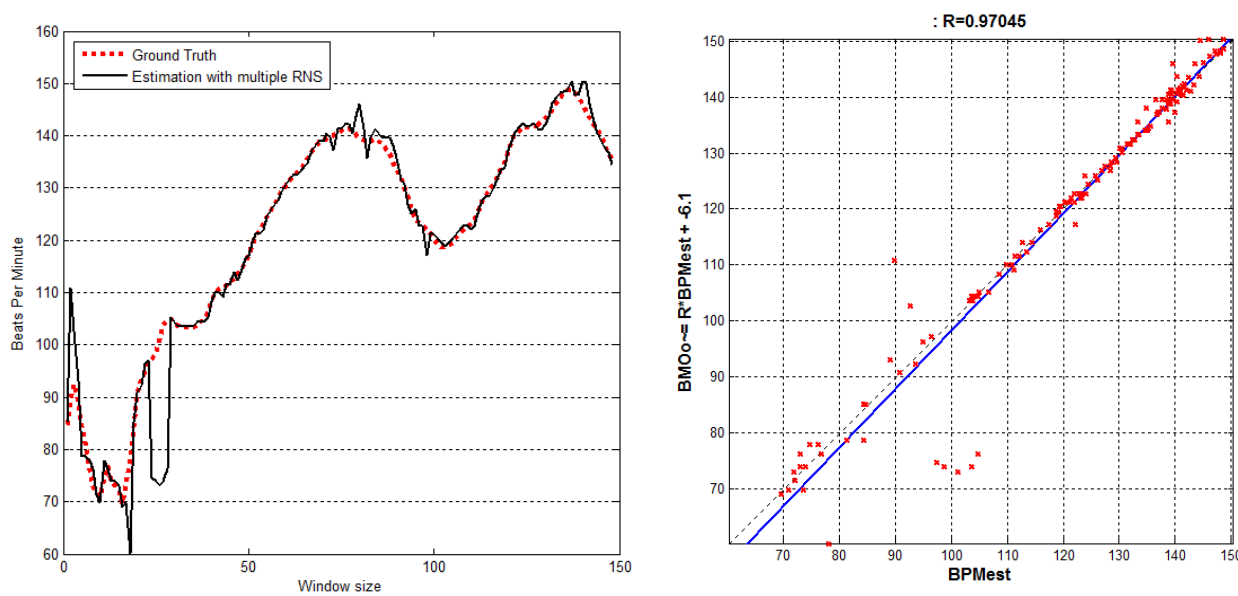
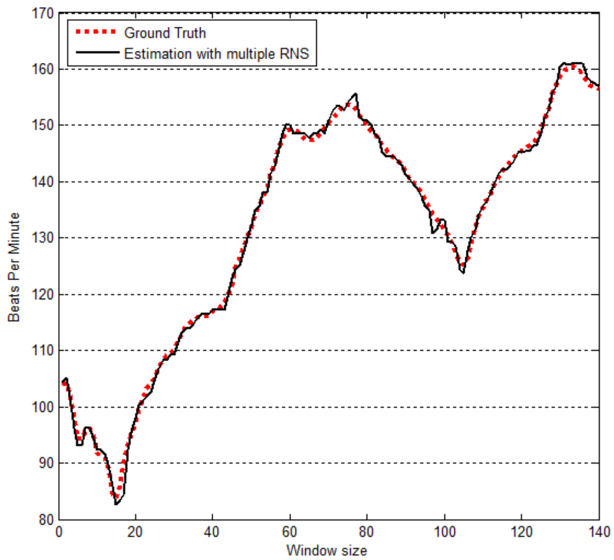


Figure 26 Estimation result on test subject 2 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot



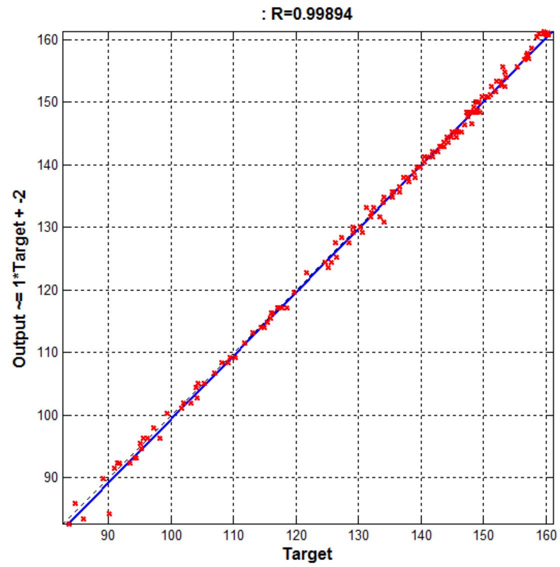
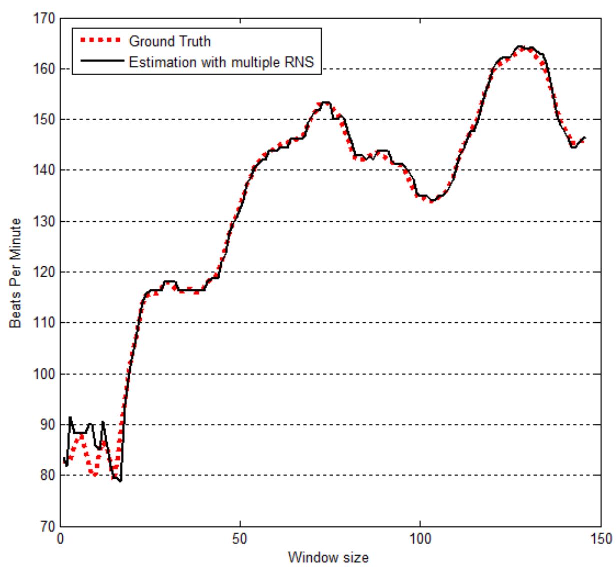


Figure 27 Estimation result on test subject 3 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot



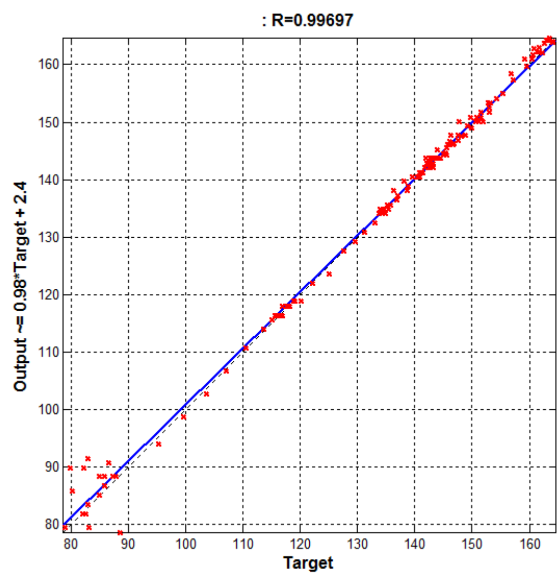


Figure 28 Estimation result on test subject 4 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

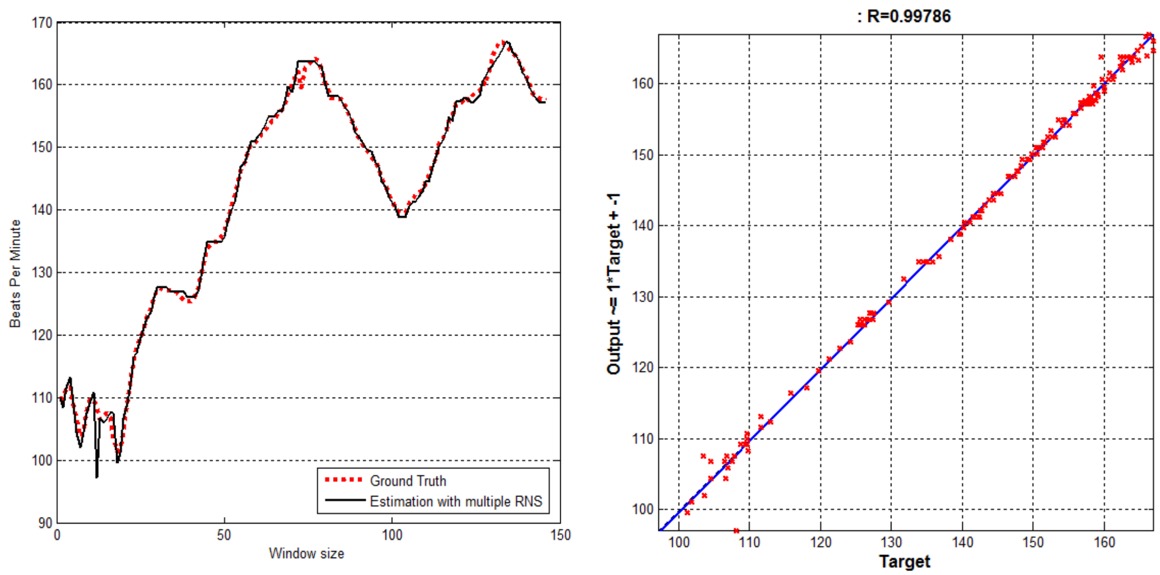


Figure 29 Estimation result on test subject 5 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

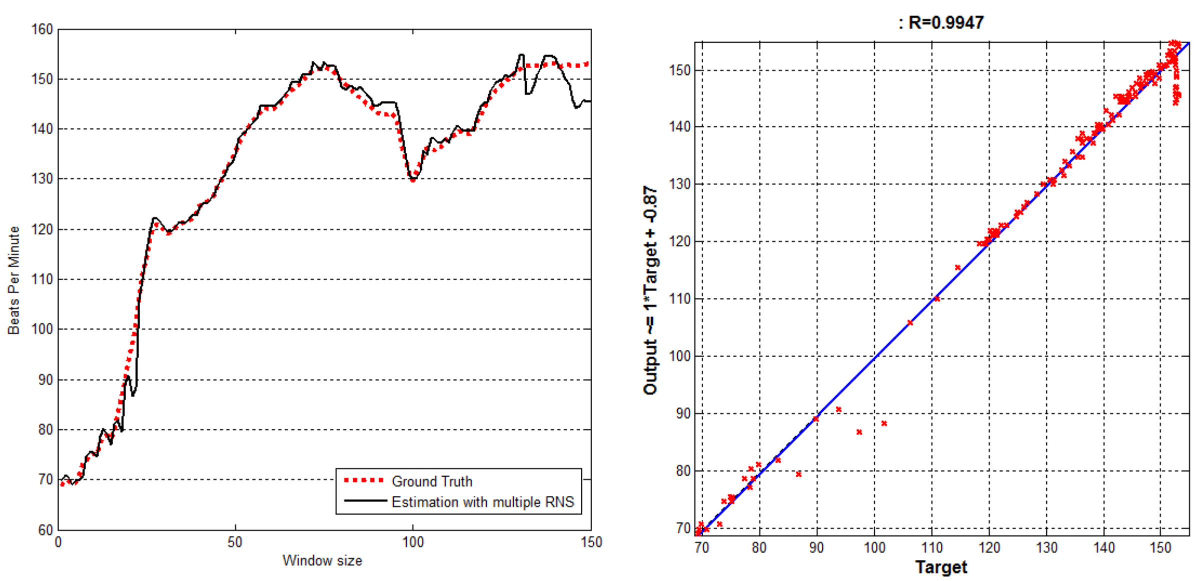


Figure 30 Estimation result on test subject 6 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

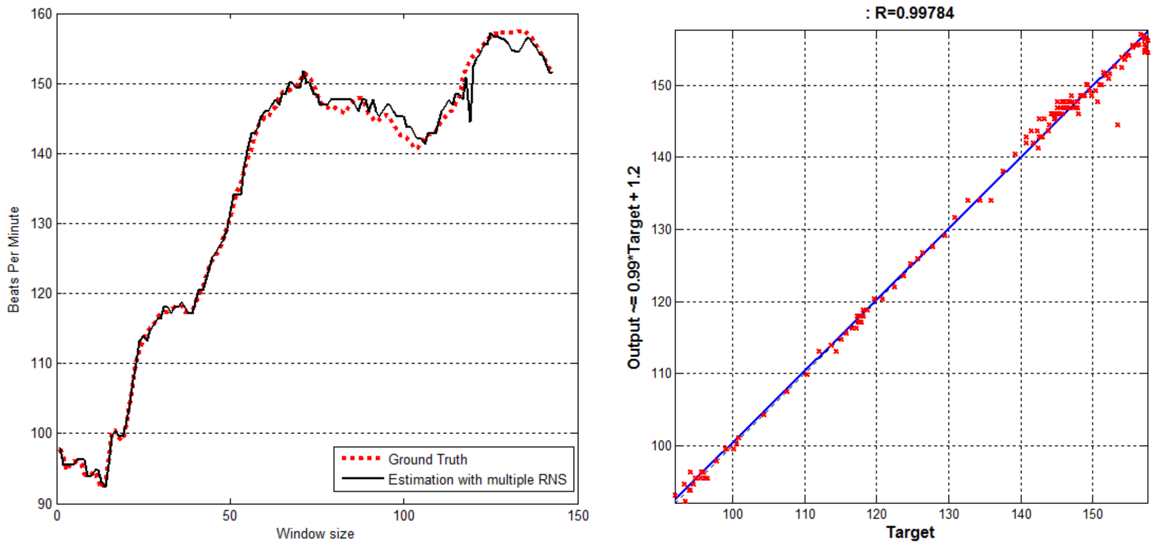


Figure 31 Estimation result on test subject 7 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

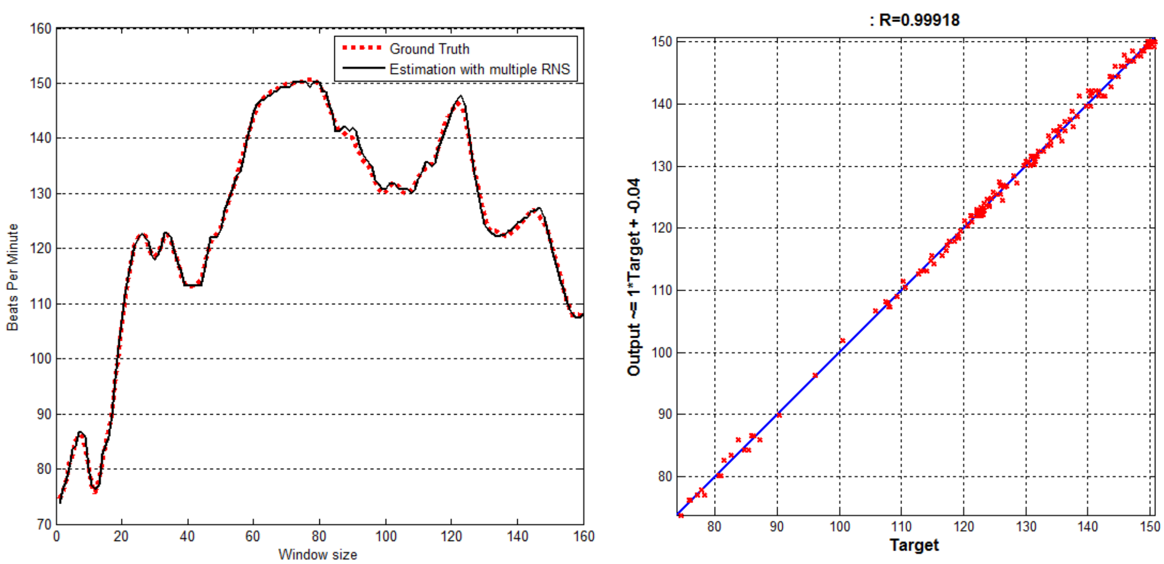


Figure 32 Estimation result on test subject 8 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

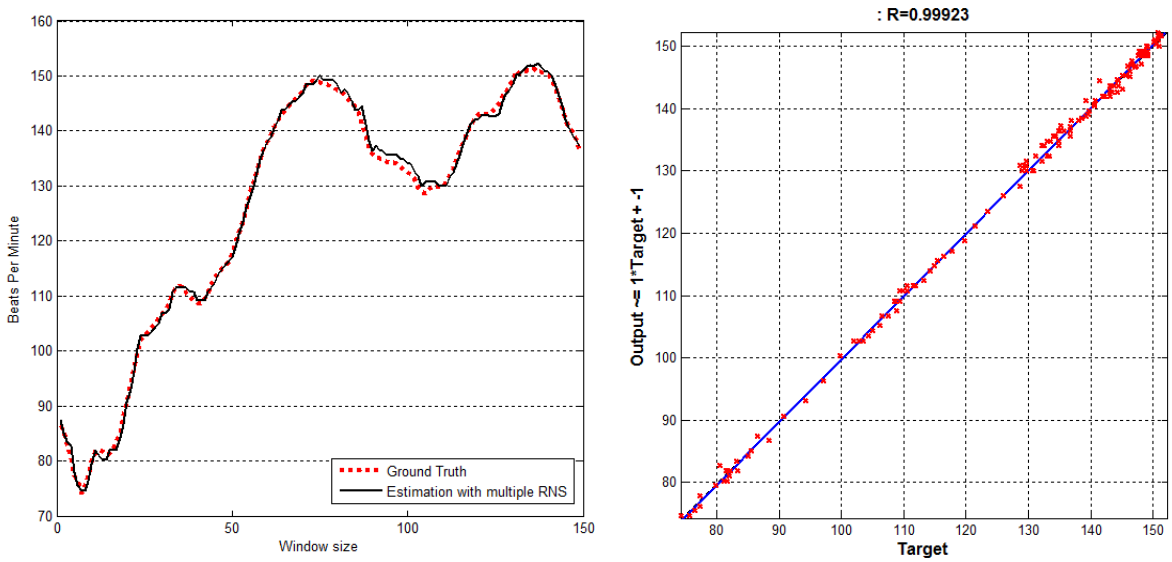


Figure 33 Estimation result on test subject 9 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

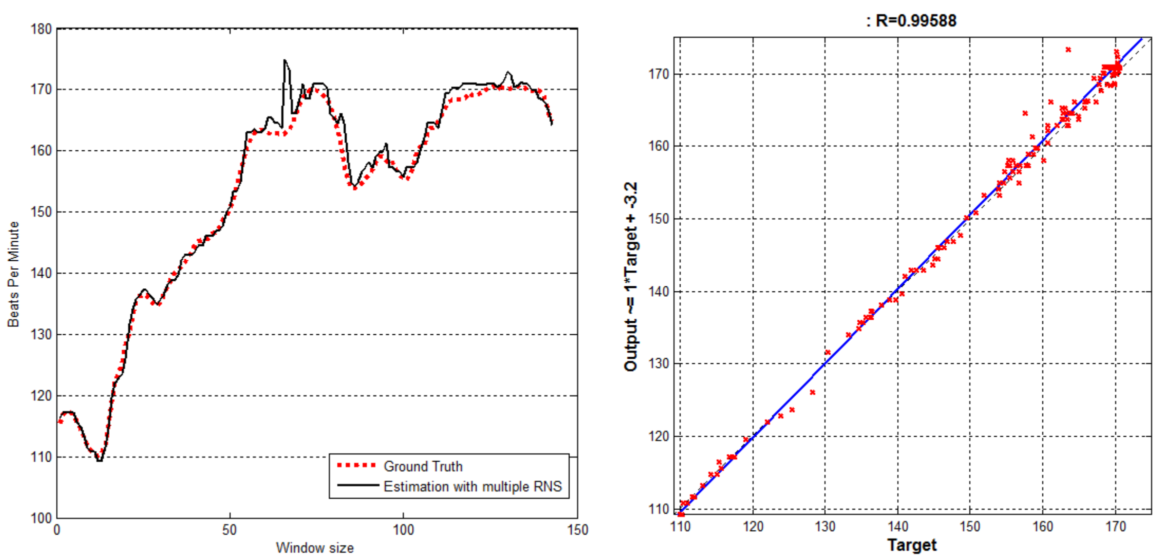


Figure 34 Estimation result on test subject 10 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

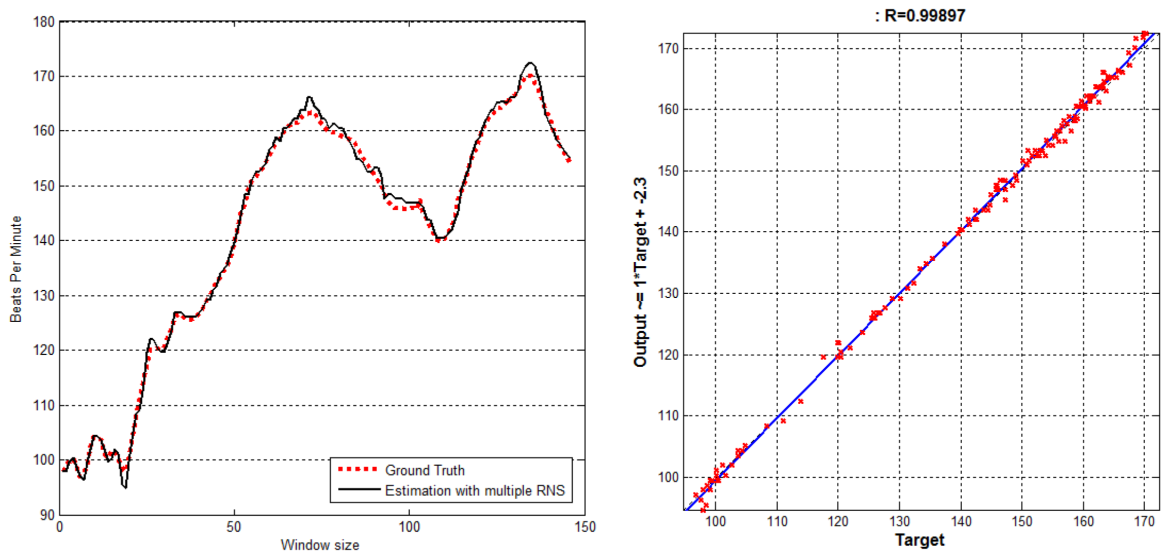


Figure 35 Estimation result on test subject 11 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

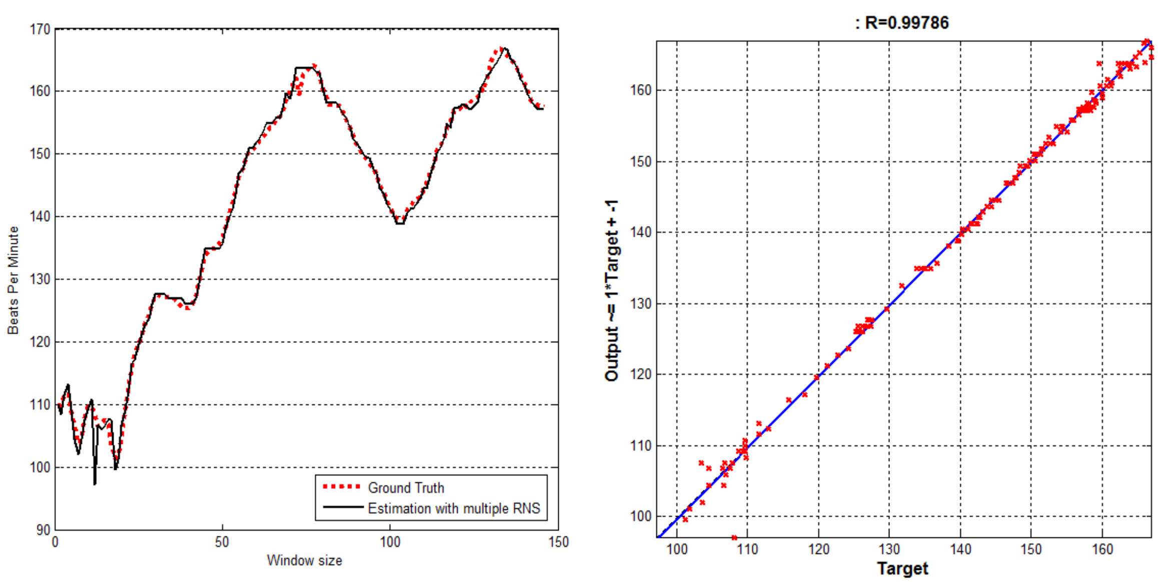


Figure 36 Estimation result on test subject 12 with ground truth of Heart rate calculated from ECG and its corresponding Scatter plot

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