

Biomedical Implantable Low-Power Fault-Tolerant Systems

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Abstract: The study provides an Independent component analysis strategy for filtering out artefacts and decoupling the Electrocardiogram (ECG) from the Ballistocardiogram (BCG) signal. The Independent Component Analysis (ICA) block is used to decompose the original signals (BCG+ECG). An initial 100 iterations are used to update the random values used to define the mixing and un-mixing matrices until convergence is reached. The mean and standard deviation are used to evaluate the filtering performance of a BCG signal. The J-J interval, I-J-K interval, RJ interval, and heart rate are identified in the BCG signals after they have been recovered from the ICA block. We have used these findings to determine if the signal originates from a healthy or unwell individual. The patient's aberrant condition is a strong argument for the use of implanted devices. In this experiment, we use three distinct sensors. The BCG information is collected by placing three sensors at various depths below the flat bed on which the subject is resting. The findings are analysed by taking into account all of the sensor data, and then compared to the outcomes produced by using either of the two sensors alone.

Keywords: the Independent Component Analysis (ICA), artifacts, Electrocardiogram, Ballistocardiogram

Introduction

Not only are biomedical signals employed in the medical sector, but they are also put to use in many other contexts due to the valuable information they give about a patient's health. They are employed in medical monitoring systems to keep tabs on a patient's vitals in real time and spot potential problems before they become life-threatening. Heart rate, blood pressure, oxygen saturation, blood glucose, nerve conduction, brain activity, etc. are all measured using a variety of physiological devices. We can learn a lot about the human body's health from these measurements. Biological signals are any electromagnetic or electrical activity inside the body. Electrodes/sensors are used to collect data for diagnostic procedures like Electrocardiogram (ECG), Electroencephalogram (EEG), and Ballistocardiogram (BCG). In order to convert the signals into usable information, they are amplified, altered, processed, and finally analysed. A fault-tolerant system is one in which operations may be continued despite the failure of some component.

Ballistocardiography is a noninvasive technique [78] used to assess the mechanical motion of the body brought on by cardiac contraction during blood ejection. Cardiac output, or the "amount of blood pumped by the heart in a minute," may be detected using BCG. One of the most encouraging ways to evaluate cardiovascular health outside of clinical settings is using this method. The benefits of BCG signals in the medical area have recently been shown through studies. Recent progress in the biological sciences has piqued the interest of researchers in BCG signal processing for health status monitoring. Tables, beds, weighing scales, and chairs are only some of the many measuring methods and systems that have been devised for BCG detection and measures. Although weighing scales offer some promise as a BCG signal measuring tool due to their low implementation cost, compact size, etc., they are still susceptible to artefacts induced by subject movement or motion during signal acquisition or by floor vibrations. For health monitoring and clinical treatment, the development of innovative portable and implantable biomedical equipment is crucial to lowering healthcare costs without compromising quality.

The Ballistocardiogram data collection is obtained from Georgia Institute of Technology and used to conduct the experiments. Seventeen typically functioning and aberrant individuals' data are included in the collection.

The Ballistocardiogram data set was collected in a variety of settings, including when the subject was seated, lying down, and even wearing the device. Most implanted embedded systems operate on batteries, therefore low power consumption is essential for biomedical signal processing. Fault-tolerant architecture allows for continued operation while using much less energy. Therefore, we suggest developing a low-power fault-tolerant system for BCG signal transmission in biomedical implants. A proof-of-concept for a low-power, fault-tolerant system for biomedical implants is the primary topic of this article. It is necessary to preprocess the obtained biological signals. The following are the design solutions considered. To conduct our experiments, we took into account data collected from the same individual while lying supine. Using these three sensors, we are able to extract a dataset of a single human being. The voltage level is not present in the retrieved data. An A/D converter is used to transform raw analogue data into digital form.

Data in digital form is transformed into voltage levels through preprocessing. The information is therefore rendered in a usable format. This information is preprocessed using an interpolation method [79]. The research suggests many preprocessing methods, including spline interpolation, cubic spline interpolation, and linear interpolation. The Spline Interpolation method yields the best possible outcome. The term "noise" or "artefacts" is used to describe extraneous or irrelevant data that causes distortion of the retrieved signal [80]. The source of the noise might be natural or artificial. Before making a diagnosis, it is crucial to get rid of all the background noise and artefacts. Because of this, we suggest a variety of FIR filter structures, including the pipelined direct form Finite Impulse Response (FIR) filter, the transposed FIR filter, and the FIR filters with 2, 3, 4, 5, and 6 taps, all of which are effective in suppressing noise. Delayed Least Mean Square (DLMS) adaptive filters are designed to get the best possible outcomes. By continuously adjusting the weight, the adaptive filter is able to filter out any unwanted noise in the data. The DLMS adaptive filter allows for operation at only 1.48W. The proposed structure is made up of error computation blocks and Finite Impulse Response (FIR) filters. We use MATLAB to do simulations of the proposed method. It produces the superior weight update parameters in line with the original filtered signal, and it performs well in terms of error computation and elimination. Using the Xilinx ISE simulator, the system has been built for 2-Tap, 3-Tap, 4-Tap, 5-Tap, and 6-Tap filtering. Power delay and frequency are used to assess the model's performance. The study includes the performance metrics like Mean Square Error (MSE), Mean Absolute Error (MAE), and Peak Signal to Noise Ratio (PSNR). The adaptive filter's output could include artefacts that prevent a correct diagnosis from being made. Artefacts are often brought on by things like motion, muscle action, vibrations, etc. Both BCG and ECG information was included in the final data set.

Biomedical signals are real-time measurements and analyses of biological processes in live organisms. Extraction of useful information from a biological signal is the main goal of biomedical signal processing. Clinicians need information on the patient's oxygen saturation, blood pressure, heart rate, nerve conduction, blood glucose, brain activity, and so on, and these physiological tools help them get it [1]. The goal of biomedical signal processing is to help clinicians make better judgements about their patients' health by gathering and analysing relevant data. Low power circuit design, fault tolerance, preprocessing, Interpolation, compact size, noise, and artefacts are only some of the obstacles that must be overcome while developing a biomedical processing system. Since most embedded systems rely on batteries, low-power implementation has become essential in the field of biomedical signal processing. The goal is to maximise battery life [2–6] without significantly impacting system performance or cost. When one component of a system fails, the rest may keep running thanks to the fault-tolerant architecture. Fault tolerance's ultimate goal is to enable self-stabilization leading to an error-free state. The retrieved signal is distorted because of vibrations introduced during data collection. If there are additional vibrations, the signal quality will suffer. Therefore, the recovered signal might include artefacts and noise. Preprocessing the retrieved biological signals is necessary so that they may be represented as voltage. It's one of the first things you do, and it's crucial to making sure the rest of the processes go off without a hitch. An Implant is a man-made substitute for a natural biomedical structure or a device used to maintain a natural biomedical structure. Artificial implantable devices are constructed from biomedical materials like titanium and silicon. Biomedical implants include things like artificial pacemakers and cochlear

implants to help the hearing-impaired. Electrodes or sensors are used to glean physiological signals. The ECG signal may be extracted using a wide variety of electrodes, and the BCG signal can be extracted using a wide variety of sensors. These signals use a noninvasive way to extract the signal, which is one of its advantages. A non-invasive technique is one that does not need any cuts or tissue removal.

Using [8-10] signal processing methods, this work aims to develop a Ballistocardiogram methodology to assess cardiac function. The BCG method is used to provide a visual picture of the regular bodily movements caused by the jarring ejection of blood into the arteries with each heartbeat. It is a surface vital sign that may be measured noninvasively and in the 1-20 Hz frequency range due to the mechanical movement of the heart. This BCG signal was developed by Dr. Isaac Starr. Starr claims that the BCG signal may be used to determine the impact of major cardiac abnormalities. Methods of BCG signal extraction [11] are shown in Figure 1.

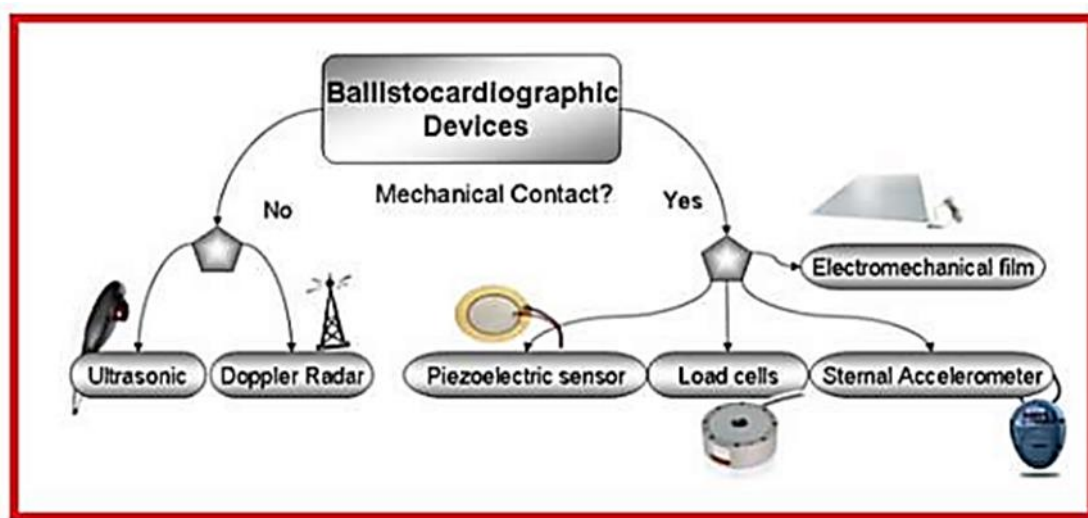


Figure 1: Ballistocardiogram signal extraction methods

Literature Survey

M. Modarressi et al.2016 ECG analysis and monitoring using a neural network technique was presented for use in real-time online. The design uses a low-power approach for implementation. The proposed low power approach is based on the realisation that a substantial portion of the calculations needed for neural network based ECG monitoring are redundant and may be disregarded. In this section, we discuss the two causes of redundant computing. Both the training set and the neuron weights are used. For online ECG analysis, which is essential for implants or wearable healthcare devices, the suggested design eliminates unnecessary processing to achieve great powerefficiency. The MIT-BIH database is mined for information and used to conduct experiments. The suggested technique decreases the power consumption of ECG analysis by 45%, as shown by the waveforms of electrocardiograms. The suggested neural network technique is low-power and, as we see it, has applications in the development of implantable and wearable devices for use in cardiovascular monitoring systems. Simple, dependable, and low-power filter-based system design yields superior outcomes.

Rui Zou et al.2016 tested how well a Cardio Chip could record an electrocardiogram. This cardiac chip is intended for use in portable settings. It's a typical 12-lead electrocardiogram (ECG) recording device with a single-channel, low-power, tiny ECG system-on-chip (SoC). R-peak amplitudes evaluated by two devices revealed statistical agreement, despite the Cardio Chip ECG's greater sensitivity to background noise compared to a medical standard ECG. The good correlation between the two ECG recordings is supported by the results of an offline analysis of signal correlation coefficients and coherence, which are both around 0.94 on average. According to the findings, Cardio Chip ECG is on par with gold-standard ECG used in hospitals. Therefore,

users may learn about and characterise their heart rate and rhythms with the use of a mobile device equipped with an inbuilt Cardio Chip. The widespread use of this technology has the potential to raise general consciousness about heart health and reveal previously undetected cardiac problems at an early stage. According to the research, the correlation coefficients between ECG and BCG are quite similar. The Cardio Chip may be utilised for this analysis of BCG accuracy.

Shashi Kant Sharma et al. 2014 Employing a number of different methods, they presented an adaptive filter. The primary goal of each of these algorithms is to eliminate background noise. Sinusoidal, chirp, and sawtooth signals are addressed in terms of the Least Mean Square (LMS), Normalised Least Mean Square (NLMS), and Recursive Least Squares (RLS) algorithms, respectively. The convergence rate and Minimum Mean Square Error (MMSE) of the developed filter have been compared. We found that the characteristics of each wave are distinct via our analysis. MATLAB and SIMULINK are used to create and test the models. Out of the three algorithms tested, RLS was shown to have the highest convergence rate, followed by NLMS and LMS. We draw the conclusion from this that saw-tooth signals are superior than sinusoidal and chirp signals for noise cancellation.

Seema Nayak et al. 2012 Various strategies for preprocessing ECG signals have been suggested, and these methods are being employed in a broad range of ECG analysis systems. In order to prevent the base line from straying, these methods make use of the wavelet transform. Inadequate grounding of ECG machines leads to power line interference. A notch filter may be used to get rid of it.

Motivation and Problem Approach

According to the study, over six lakh individuals die annually from cardiovascular disease, and almost seven lakh people are affected by it. Improved ECG technology has allowed for a 41% reduction in mortality rates. Ballistocardiography has been cited in a number of studies as a useful tool for diagnosing heart conditions at an early stage. Therefore, the mortality rate may be managed by the use of preventative measures if the condition is detected early. This is why we decided to focus on biological signals as our field of study. Preprocessing biological signals presents a number of difficulties. The raw data is transformed into a format that can be processed more efficiently and readily by the user via preprocessing. Preprocessing is crucial since most actual medical data is very noisy, fragmentary, and inconsistent. The authors of this study suggest many preprocessing procedures, including Linear, Cubic, and Spline Interpolation. Therefore, these methods provide superior outcomes [8]. When using a BCG measuring system, motion artefacts and vibrations are often the most problematic factors. Artefacts occur when the subject moves while the signal is being acquired. The measured signal is less clear and understandable due to the vibrations that create the noise. In light of this, we've developed an adaptive FIR filter to eliminate noise. An adaptive Least Mean Square method with a weight updating process was suggested by Widrow et al. The adaptive Least Mean Square technique is easy to understand and implement. LMS algorithm performs better than other algorithms when it comes to solving convergence problems. Delayed Least-Mean-Squares Adaptive Filter (DLMS) is an alternative method of signal filtering. When compared to the LMS algorithm, the DLMS method provides superior filtering performance. The critical route latency is DLMS's primary shortcoming. Pipelined design is able to shorten the latency of the critical route [12]. The pipelined design is implemented depending on the filter's sampling rate. In order to isolate the original signal, this study suggests using Independent Component Analysis (ICA). One of the purposes of the ICA method is the removal of artefacts. Heart and brain signals (ECG and BCG) are the original data. Since the original ECG signal is included in the BCG data, an ICA model is used to decompose the two signals [13]. Separate analyses of the BCG and ECG signals remove the various peaks needed for a disease diagnosis. Taking sensor output into account allows for the development of a fault-tolerant system, essential for any biomedical application. When compared to alternative literature survey techniques, the findings collected lead us to infer that the adopted strategy is superior.

Research Methodology

Sensors are positioned at various locations on the bed, chairs, or the body (if wearable) to collect data..

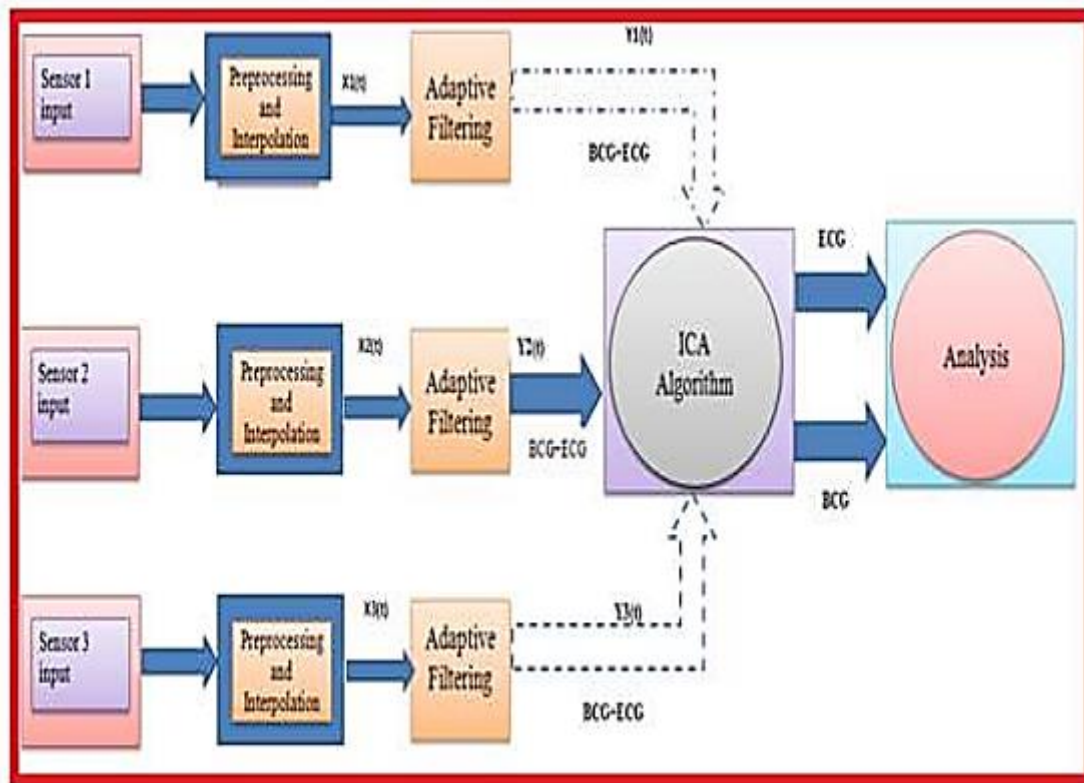


Figure 2: Block diagram of proposed work

Georgia Institute of Technology provides the BCG dataset needed for the laboratory setup. Both men and females are present in the dataset. The suggested work does experimental analysis using these datasets. The dataset comprises the health information of 17 individuals, 10 men and 7 women, with a mean age of 23.6 4.5 years, a standard deviation in height and weight of 172.8 9.9 cm and 70.7 11.3 kg, respectively.

LMS adaptive filter is fed the cleansed data. The proposed architecture has functional units that compute errors and FIR filters. As a filtering algorithm, we have used the 2-tap, 3-tap, 4-tap, 5-tap, and 6-tap approaches. The MATLAB programme is used to accomplish this strategy. Error calculation efficiency is shown, and a superior weight update parameter, which is in line with the unfiltered signal, is achieved using the proposed technique. The retrieved signal has had 80% of its noise removed. The initial signal is distorted for numerous reasons throughout the acquisition process. The noise introduces artefacts into the base signal [11], making analysis and monitoring more challenging. This thesis presents an Independent Component Analysis (ICA) method for artefact elimination to deal with this problem. Using MATLAB, we model the design, and then we conduct the experiment on many different persona datasets. The filtering performance of this approach is superior. Separation of the ECG and BCG signal is suggested using an ICA algorithm. The normal and abnormal states of the individual are determined by analysing this data. The patient's aberrant condition is a strong argument for the use of implanted devices. Power requirements for implanted devices vary depending on their function. Pacemakers need between 11W and 2mW of power [7]. Power consumption for a ventricular assist device (VAD) is 5-25.0W, whereas that for a retinal prosthesis is 45.0mW.

FPGA Implementation of BCG Signal Filtering

There has been a steady rise in cardiac issues recently. Monitoring and measuring heart activity using electrocardiogram (ECG) is the standard. Therefore, Ballistocardiogram (BCG) is proposed as an alternate approach to monitor cardiac function in this thesis. In the case of biological signals, isolating the needed signal from artefacts and sounds is a challenge. Muscle artefacts, baseline drifting, power line interference, and electrode artefacts all contribute to the background noise. Different kinds of digital filters are employed to isolate the signal from the background noise and artefacts. For signal filtering of BCG signals, we offer an FPGA implementation of Pipelined direct form FIR filters, Transposed FIR filters, and an Adaptive filter scheme. The noise around a BCG signal is made up of low-frequency components, typically between 0.5 Hz and 100 Hz. The low-frequency noise reduction capabilities of the suggested digital filters in the thesis are impressive. We have relied on FIR filters because of their low cost and high sample throughput.

Experimental Results

In this paper, we explore the suggested method for filtering BCG signals. The IEEE standard VHDL language is utilised to implement this method, with Xilinx ISE used for simulation and synthesis. Xilinx ISE V14.3 is used for simulation of the proposed filter design. The Virtex-V family, namely the XC5VSX95T device in package FF1136, speed grade -2, is employed in this simulation research. The filtering methodology is fully developed throughout the thesis. Based on these findings, we infer that the custom-made filter effectively cleans up the data. In this case, we conduct the experiment over three distinct data sets. Each BCG signal for a cardiac contraction will have its own unique pattern of peaks and valleys since each signal represents a unique event.

Various simulation parameters are considered to generate the data which are given in table. 1

Parameter	Values
Total Beats	5
Threshold of Peak	0.6
Left Side window	0
Right Side window	700
Sampling frequency	1000
stop band Frequency 1	0.2
Pass band frequency1	1.0

Table 1: Simulation parameters

Simulation Results Obtained

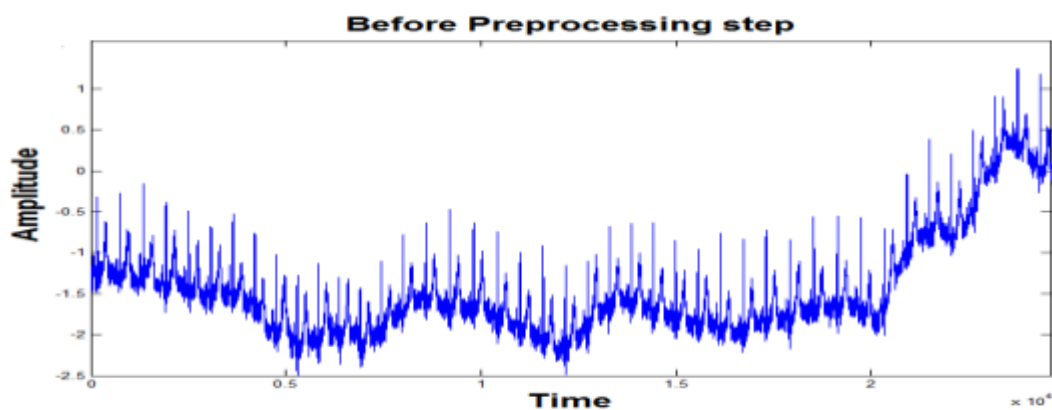


Figure 2: Extracted Raw Data of sensor1

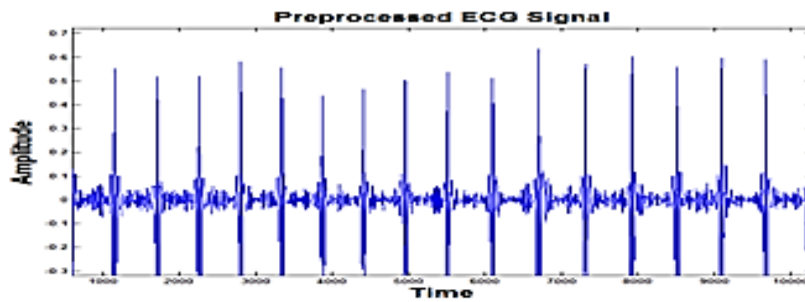


Figure 3: Preprocessed ECG signal

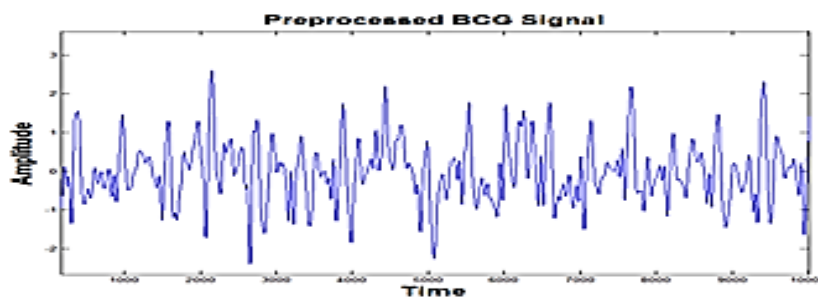


Figure 4: Preprocessed BCG signal

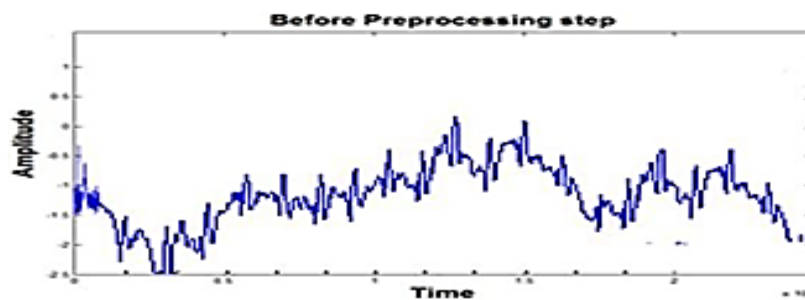


Figure 5: Extracted Raw Data of sensor 2

Figure 2-5 depicts the two sensor outputs. These signals are being examined as potential input to a noise-reduction adaptive filter. However, the extracted signal may have been contaminated by artefacts due to subject motion. Independent component analysis can get rid of it.

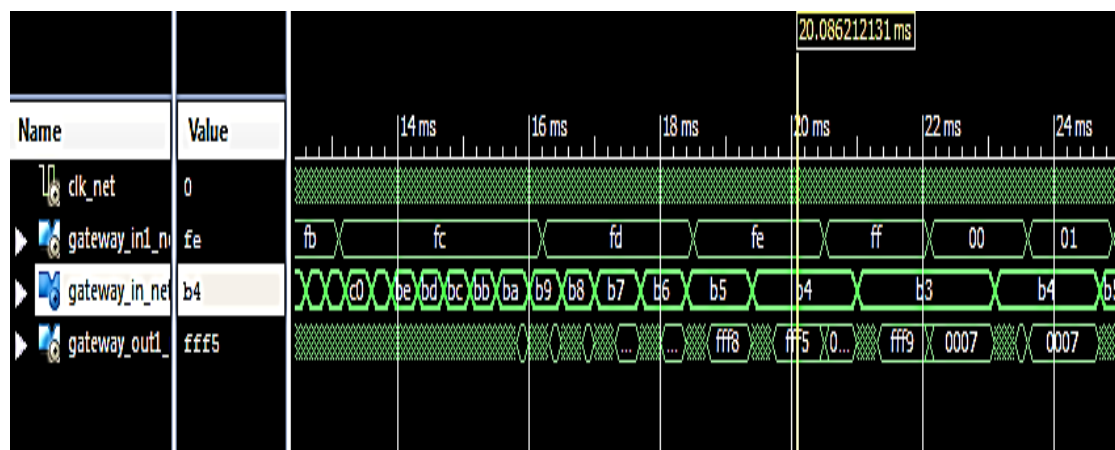


Figure 6: Simulation Waveform for proposed DLMS filter architecture

Timing summary, device utilization Summary and power consumption details for 2,3,4,5 and 6-tap of filter using FPGA is presented in figure 6

Conclusion

Preprocessing methods are used to transform A/D data into voltage levels. To get a voltage range of 5V, 23 bits are utilised in preprocessing. The thesis takes several bit depths into account during processing, including 8 bits, 16 bits, 24 bits, and 32 bits, yielding a voltage range of 161890.1, 630.38, 2.47, and 0.00965 correspondingly. To fill in the missing data point with the available discrete collection of known data points and to smooth the resultant BCG wave, the author presents Linear Interpolation, Spline Interpolation, and Cubic Spline Interpolation algorithms. Since the H, I, J, K, and L peaks of the BCG wave were preserved throughout the smoothing process, the resulting result indicates that Spline Interpolation is an appropriate method for this task.

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