Denoising of PPG Signal using wavelets in VLSI technology

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ABSTRACT: Denoising of wavelet represents a common processing step performed in various applications in the field of biomedical engineering. Wavelet denoising represents a common preprocessing step for several biomedical applications exposing low SNR. These applications require real time processing along with minimization of power and area, only custom VLSI implementations can be adopted for this fulfillment. In this paper, Photoplethysmography (PPG) signal is used as a biomedical signal as an example. PPG is a non-invasive method in which relative blood volume changes in the blood close to skin is measured. The “pulse waveform” never underwent intensive investigation. Active investigation efforts are opening to reveal its effectiveness beyond oxygen saturation and determination of heart rate. With the introduction of pulse oximeter, this is one of the important waveforms that are normally displayed in the clinical settings nowadays. But, the acquired PPG signal using PPG sensors are usually corrupted with different kinds of interference like Motion Artifacts, Power Line Noise, etc. We consider Power Line Noise for the performance evaluation of VLSI Wavelet based denoising of PPG signal. Different kinds of Wavelets such as db4, Coif1, Haar for denoising. Also, standard deviation and mean absolute deviation are used as evaluation criteria. Xilinx ISE for DSP is exploited for the design of the architecture and simulation of proposed denoising method.

Keywords: EEG,ECG-PPG, DWT, Spartan 3E.

I. INTRODUCTION

1.1. Importance of VLSI in Biomedical Signal Processing

Biomedical signal processing aims at extracting the information embedded into a physiological measurement, typically in order to aid the diagnosis, monitor a patient or control an electronic device that, at a certain level, interacts with the patient in real time. For such a processing it requires wearable or implantable electronics. With the increasing integration capabilities and the advancements in CMOS processes, it is progressively becoming more common. Applications like electrocardiography (ECG) 1 and electroencephalography (EEG) 2 often require these features. This requirements can be solved by the development of a low-power Application Specific Integrated Circuit (ASIC). Compared to microprogrammed solutions involving the use of microcontrollers or low-power digital signal processors (DSP), ASIC design requires highly specific skills and a longer development time 3, unfortunately leading to nonflexible architectures.

1.2. Wavelet Transform and Discrete Wavelet Transform

The continuous form of WT for a signal x(t) is analytically defined by:

$$W(p,q) = \int_{-\infty}^{\infty} x(t)\, \psi_{p,q}(t)dt$$

$$\psi_{p,q}(t) = \frac{1}{\sqrt{p}}\, \psi* \left(\frac{t-q}{p}\right)$$

where ∗ denotes complex conjugate and ψp,q(t) is a window function called the daughter wavelet, p and q are called as a scale factor and a translation factor respectively. Therefore, ψ∗(t−q p) is a translated and scaled version of a mother wavelet ψ(t), and for wavelet decomposition of a signal this is used as a basis. However, certain amount of redundant information is provided by the continuous wavelet transform. For most pracical purposes therefore, Discrete form of WT known as DWT is sufficient, that provides adequate information and a considerable reduction in the computation time is also achieved. For a discrete function x(n), it is given by:

$$W(p,q) = C(a,b) = \sum_{n \in Z} x(n)\psi_a$$

where ψa,b(n) presents a discrete wavelet defined as ψa,b(n) = 2 −a 2 ψ(2−an−b). The parameters p, q are defined as p = 2a and q = 2ab. The Wavelet Transform has huge number of applications in Science, Engineering, and Mathematics. It plays a vital role in biomedical signal processing, and an extensive review of the approaches can be found in Makris, C. 4 & Merry, R.J.E. 5. Also results of the studies have demonstrated that the WT in its discrete form Discrete Wavelet Transform (DWT) is the most promising method in such applications.

II. LITERATURE SURVEY

A comprehensive survey of wearable and wireless ECG monitoring systems for older adults.

Abstract : Wearable health monitoring is an emerging technology for continuous monitoring of vital signs including the electrocardiogram (ECG). This signal is widely adopted to diagnose and assess major health risks and chronic cardiac diseases. This paper focuses on reviewing wearable ECG monitoring systems in the form of wireless, mobile and remote technologies related to older adults. Furthermore, the efficiency, user acceptability, strategies and recommendations on improving current ECG monitoring systems with an overview of the design and modelling are presented. In this paper, over 120 ECG monitoring systems were reviewed and classified into smart wearable, wireless, mobile ECG monitoring systems with related signal processing algorithms.

III. EXISTING METHODOLOGY

The existing system are follows as High power consumption due to not using of specific filters to processing of medical signals. Complexity is very more when it is implanted in hardware medical applications. Designing and implementation of circuits are difficult. Replacement of device is difficult since components are costly. Then transportation of equipments are not possible. Only few diseases are examined.

Photoplethysmography-Based Heart Rate Monitoring in Physical Activities via Joint Sparse Spectrum Reconstruction. This deals with the Wearable Health Monitoring. VLSI Wavelet Based De-noising of PPG Signal performs using Wavelet transform. In this Real-time implementation of discrete wavelet transform on FPGA deals with Wavelet transform, hardware implementation.

Signal processing in VLSI.

The main aim of this process is extracting the information and then converting into physiological measurement. To diagnosis, monitor and interact with patient in real time it need wearable or implantable electronics devices. By using CMOS technology it is made possible. But it will be consuming more power. To overcome this power consumption, application specific integrated circuit is introduced. But the designing of application specific integrated circuit architecture is complex.

IV. PROPOSED METHODOLOGY

4.1. Real Time Denoising Architecture

DWT be successfully used in filtering of the signal, here called as “denoising”. It consists of four successive steps: signal decomposition, threshold estimation, thresholding, and signal reconstruction. However, the intensity of the noise was estimated with the second level wavelet coefficient as this matches to the frequency band of a narrow-band Power Line noise signal The architecture for real time denoising of a signal is as shown in Fig. 1.

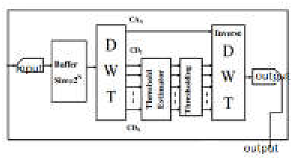
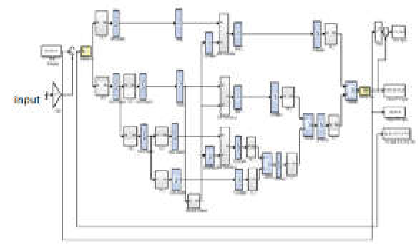


Fig. 1: Real Time Denoising Architecture.

4.2. Wavelet Decomposition/Reconstruction

For the proposed wavelet based denoising system a three level decompostion-reconstruction tree is realized. However, the intensity of the noise was estimated with the second level wavelet coefficient as this matches to the frequency band of a narrow-band Power Line noise signal. Fig. 2 represents a real time implementation wavelet based denoising technique using Xilinx System Generator blockset. It consists of a pair of Lowpass Ld and a High-Pass Hd filters for the decomposition at each level. For each j th decomposition level following i, the Ld and Hd filters a downsampling operator ↓ 2 is used that represents the decrease of a sampling rate by 2. For each j th decomposition level CAj and CDj represents the approximate and detailed coefficients respectively.

For the reconstruction of the signal first the threshold is estimated using second level wavelet coefficient followed by applying suitable thresholding technique to all the levels of wavelet coefficients then upsampling denoted by upsampling operator ↑ 2 and finally filtering by filters Lr and Hr. All the filters are characterized by the values of their coefficient and these values are typically be floating point, with different vector lengths and can differ from the simplest ones like Haar, to a slightly complex Daubechies upto those like Quadartic Spline. As mentioned in Section 2 the proposed architecture also equalizes the filter path delay using delay operators . this paper presents a real-time architecture for forward/inverse wavelet transforms that take into account the group delays of the used filters. The main idea is based on the equalization of the filter path delays. The perfect reconstruction of this architecture was evaluated for various data widths. This architecture was implemented on FPGA using XUP Virtex-II Pro development board.



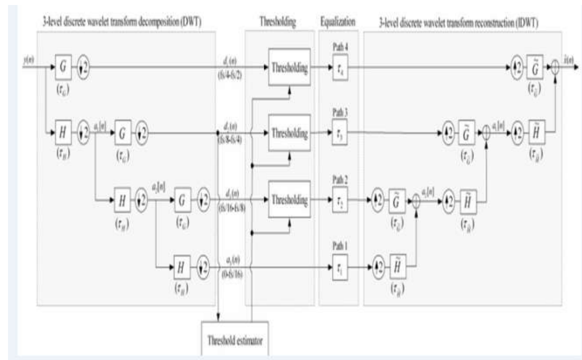


Fig. 2: Wavelet Based Denoising Technique Implemented using Xilinx System Generator Blockset.

4.4 Result Analysis

For evaluating the performance of the proposed denoising method, it is processed in few stages as shown in Fig. 3. The database consists of PPG signals downloaded from PhysioBank ATM15. Then, 60 Hz noise signal is added to the PPG signal as a source of interference. The attributes of the signals before and after denoising is extracted. The

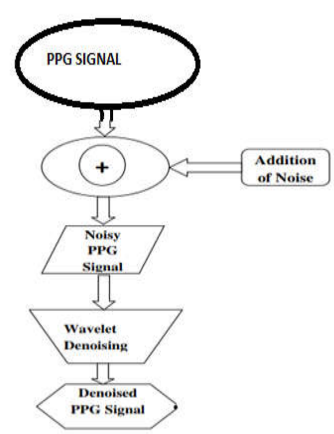


Fig. 3: Block Diagram to represent stages of processing denoising method.

mean absolute deviation which is given by equation 7 and standard deviation of a data set which is the square root of its variance, are used as a evaluation criteria as shown in Table 1 for different wavelets.

Mean Absolute Deviation $=\frac{1}{n}\sum_{i=1}^{n} ei$

and ei is given by

$$e_i = \; x\,(i) original\ ppg\ signal - x(i) denoised\ ppg\ signal$$

where, x(i)original PPG signal is amplitude of the PPG signal before denoising, x(i)denoised PPG signal is amplitude of the PPG signal after denoising and "n" is the total number of points in the data set (here, total number of samples in the PPG signal).

There is a rapid growth in the field of Bio signal processing with increase in the understanding of a complex biological process in a broad diversity of areas. Different WT functions are a powerful time frequency approach. In this paper this has been applied to PPG signal preprocessing. The signal reconstruction is however, more exact in db4 wavelet transform whereas others are less effective for the signal under consideration. The mean absolute deviation of the denoised signal using db4 wavelet transform is close to the input PPG signal than other wavelets.

V. RESULTS

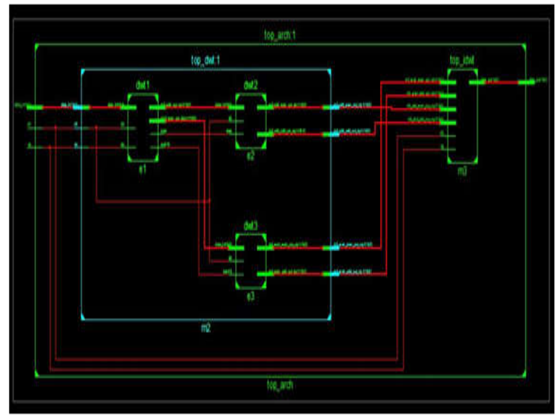
PROPOSED RESULTS:

SYNTHESIS RESULTS:

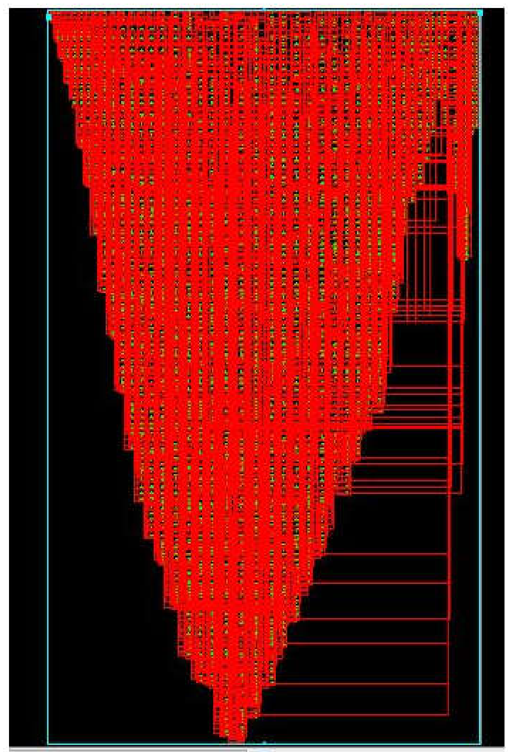
The developed project is simulated and verified their functionality. Once the functional verification is done, the RTL model is taken to the synthesis process using the Xilinx ISE tool. In synthesis process, the RTL model will be converted to the gate level netlist mapped to a specific technology library. Here in this Spartan 3E family, many different devices were available in the Xilinx ISE tool. In order to synthesis this design the device named as "XC3S500E" has been chosen and the package as "FG320" with the device speed such as "-5".

This design is synthesized and its results were analyzed as follows

RTL SCHEMATIC:



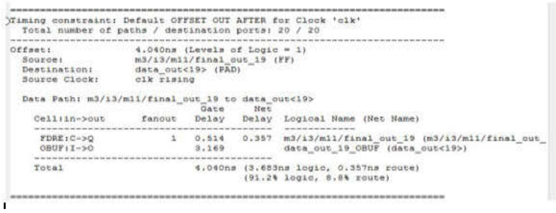
TECHNOLOGICAL SCHEMATIC:



DESIGN AND SUMMARY:

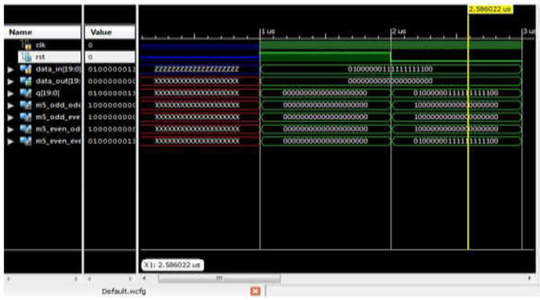
Device Utilization Summary (estimated values)			
Logic Utilization	Used	Available	Utilization
Number of Slices	811	4656	17%
Number of Slice Flip Flops	885	9312	9%
Number of 4 input LUTs	1471	9312	15%
Number of bonded IOBs	42	232	18%
Number of GCLKs	1	24	4%

TIMING REPORT:



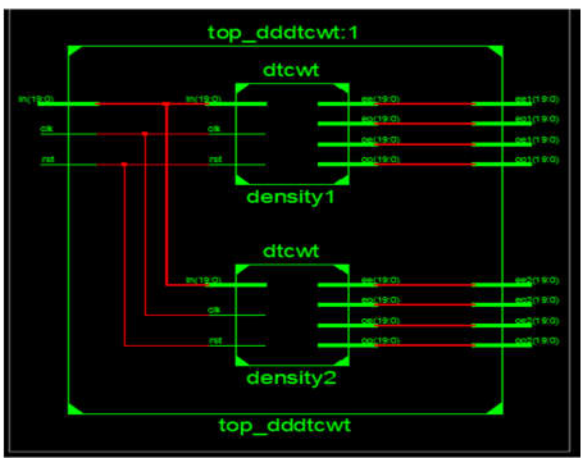
```
Timing constraint: Default OFFSET OUT AFTER for Clock 'clk'
  Total number of paths / destination ports: 20 / 20
-------------------------------------------------------------------------
Offset:              4.040ns (Levels of Logic = 1)
  Source:            m3/i3/m11/final_out_19 (FF)
  Destination:       data_out<19> (PAD)
  Source Clock:      clk rising

  Data Path: m3/i3/m11/final_out_19 to data_out<19>
                                Gate     Net
    Cell:in->out      fanout   Delay   Delay  Logical Name (Net Name)
    ----------------------------------------  ------------
     FDRE:C->Q             1   0.514   0.357  m3/i3/m11/final_out_19 (m3/i3/m11/final_out_
     OBUF:I->O                 3.169          data_out_19_OBUF (data_out<19>)
    ----------------------------------------
    Total                      4.040ns (3.683ns logic, 0.357ns route)
                                       (91.2% logic, 8.8% route)
```

SIMULATION RESULTS:

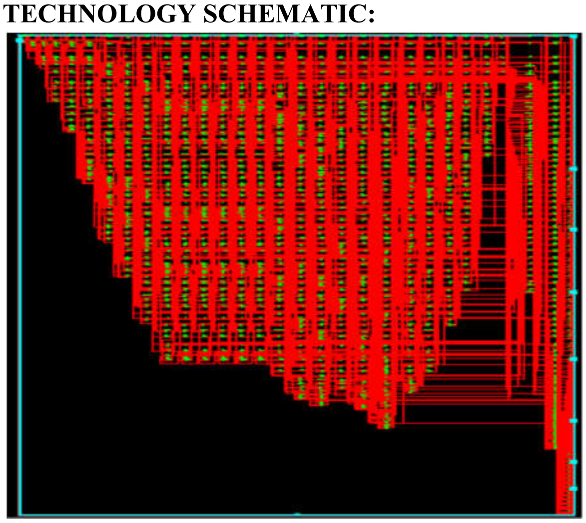


EXTENSION RESULTS:

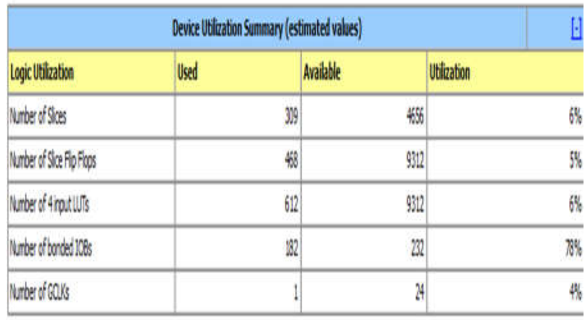
RTL SCHEMATIC:



TECHNOLOGY SCHEMATIC:

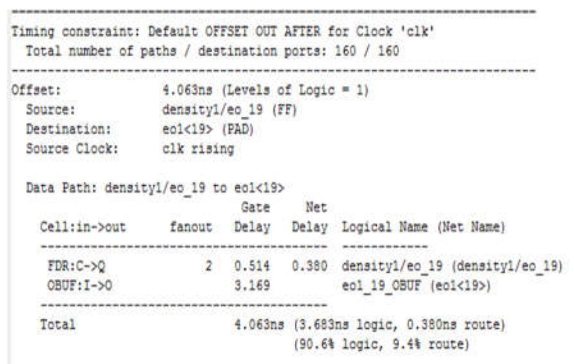


DESIGN AND SUMMARY:



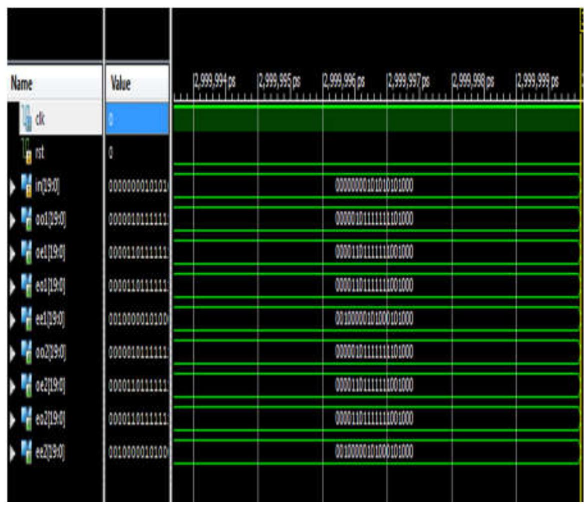
Device Utilization Summary (estimated values)			
Logic Utilization	Used	Available	Utilization
Number of Slices	309	4656	6%
Number of Slice Flip Flops	468	9312	5%
Number of 4 input LUTs	612	9312	6%
Number of bonded IOBs	182	232	78%
Number of GCLKs	1	24	4%

TIMING REPORT:



```
Timing constraint: Default OFFSET OUT AFTER for Clock 'clk'
  Total number of paths / destination ports: 160 / 160
-------------------------------------------------------------------------
Offset:              4.063ns (Levels of Logic = 1)
  Source:            density1/eo_19 (FF)
  Destination:       eo1<19> (PAD)
  Source Clock:      clk rising

  Data Path: density1/eo_19 to eo1<19>
                                Gate     Net
    Cell:in->out      fanout   Delay   Delay  Logical Name (Net Name)
    ----------------------------------------  ------------
     FDR:C->Q              2   0.514   0.380  density1/eo_19 (density1/eo_19)
     OBUF:I->O                 3.169          eo1_19_OBUF (eo1<19>)
    ----------------------------------------
    Total                      4.063ns (3.683ns logic, 0.380ns route)
                                       (90.6% logic, 9.4% route)
```

SIMULATION RESULTS:



VI. CONCLUSION

A real-time VLSI Wavelet Transform based denoising technique is proposed in this paper to remove the power-line from PPG signal. Xilinx System Generator for DSP is exploited for the implementation and fast prototyping of the proposed technique. Various wavelet functions are selected for denoising. The results of denoising is evaluated on the basis of standard deviation and mean absolute deviation. From Table 1 it is clear that the original signal and db5 denoised signal are more correlated and shows better results compared to other wavelets used in denoising the PPG signal. Hence it can be used for analyzing PPG signal. Careful analysis of the PPG signals can give us information associated to patient suffering from diabetes and arthritis. In future, more advanced methods for denoising of the PPG signal corrupted by other sources of interference such as MA, estimating the heart rate and respiratory rate by means of PPG signal will be implemented which can be used for diagnosis of patients in real time. Also these methods will be implemented and tested on real PPG signals.

VII. REFERENCES

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