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ECG SIGNAL FILTERING IN FPGA

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ABSTRACT: Electrocardiographic signal (ECG) is the most important electrophysiological signal used in the clinic for screening and diagnosis of many cardiac diseases. The signal picked up from the patient is affected by the noise, so it must be processed to be presented as clean and clear as possible to support accurate decisions by physicians.Two different filtering methods for ECG signal processing are utilized in this paper. Mean Filter with a sliding window of 16 samples, Low-pass filter with 50Hz cut off are used here in this paper to filter acquired ECG signals. Both filtering algorithms are implemented in XILINX software. Further this project is enhanced by Fuzzy-based PSO technique. Proposed coding is efficient technique which allows a compact representation of data by electively reducing the error between the data itself and information “predicted” from past observations. The prediction techniques build an estimate x'(n) for a given sample x(n) of the signal by using past two samples with low latency and less area.

Keywords: Electrocardiographic, cardiac diseases, Fuzzy-based PSO, Low-pass filter, prediction techniques.

INTRODUCTION: Fetus health condition is monitored by many methods where Electrocardiography is one of the frequently used methods which shows the fetus heart’s electrical activities. Generally, an invasive or non-invasive method of recording of Fetal ECG (FECG) is performed. In invasive method of recording, the electrode has to be placed on the scalp of the fetus to measure the ECG but the electrode has to be passed through mother’s womb which creates difficulties to the mother [1] and also possible only at the later stage of pregnancy period. The non-invasive method of recording does not provide any trouble to the mother because the electrode has to be placed on mothers’ abdomen to measure the ECG of the fetus. There are several approaches proposed to record the fetal ECG under non- invasive method which uses either a single lead or two leads or multiple leads. For a single lead method of recording, only one electrode is positioned on the mothers’ abdomen, two lead systems uses two electrodes which have to be positioned on the chest and abdomen and multiple lead systems require multiple electrodes to record the fetal ECG. There are several complications in non-invasive method of recording fetal ECG, because the recording is not directly taken from the fetus which is measured on the abdomen, hence the fetal ECG is to be extracted from signal contaminated by multiple sources of interferences. Apart from these sources of interferences the low signal level of fetal ECG [2] and the spectral overlapping of mother ECG and fetal ECG [3] makes the extraction more critical. ECG (electrocardiogram) is a test that measures the electrical activity of the heart. The heart is a muscular organ that beats in rhythm to pump the blood through the body. In an ECG test, the electrical impulses are generated while the heart beatings are recorded. The extensive use of digital electrocardiogram (ECG) produces large amounts of data. Since it is often necessary to store or transmit ECG records, efficient compression techniques are important to reduce transmission time or required storage capacity. Especially critical are long duration (24 or even 48 hours) Holterexams. The data generated in such cases can surpass 1G bytes. These Holter devices must present good storage capacity, in addition to reduced dimensions and low power dissipation in order to be comfortably carried by patients.

LITERATURE SURVEY: Time sequenced adaptive filtering has been recommended by Ferrara &Widrow [4] for FECG enrichment. They identified the non-stationary fetal ECG signal having recurring statistical characteristics. The Least Mean Square (LMS) adaptive filter can able to follow up such fast changing non stationarities, hence an adaptive filter have to be designed with rapidly varying impulse response to improve the performance of the extraction. The method uses many sets of hyper parameters to adapt for fast changing impulse response. In order to adapt for fast changing impulse response, the method requires more abdominal signals and also timely identification of estimated fetal pulse. Apart from the above requirements the technique needs prior information of fetal ECG positions. The time sequenced adaptive filtering provides more accurate results compared to classical LMS adaptive filter. The overall performance of the adaptive filter is increased when the number of channel input is increased. The main advantage of this approach is that the prior knowledge of signals' power spectrum is not required. But, the time sequenced method need the estimation for the timely identification of the pulse, to synchronize the filter regeneration and the fetal cardiac cycles. They stated the future direction to enhance the results by finding better method to locate the fetal pulse positions in order to make this approach with recordings having lower SNR. Kam& Cohen [5] identified a method to find the fetal ECG using Infinite Impulse Response (IIR) filtering technique and Genetic Algorithm (GA). The hybrid IIR-GA approach on fetal ECG extraction, the adaptation rule is combined with GA, whenever the estimated gradient stuck with local extremum. Hybrid IIR-GA provide best with simulation compared to FIR LMS based method but with real data, the method fails to show the significant difference between them. This may be because of the body transfer function acts as a simple low pass filter so that a lower order FIR adaptive filter is sufficient, and the authors suggested further studies are required to analyze this assumptions. Talha et al. [6] also presented similar approach of GA based Finite Impulse Response (FIR) filter for extraction where Genetic algorithm is used as a optimizer for FIR filter and the results are compared with the other approaches of adaptive filters like wiener filter, Recursive Least Mean Square (RLMS) and NLMS filters. The NLMS approach provide better results in terms of reliability and speed of convergence but provide divergence results when the adaptation is too large which have been overcome by the method of GA based FIR filter. GA with eight bits and ten iterations provide better quality compared to other algorithms and an improvement may be provided by changing the order of the filter. The adaptive filtering approach may be combined with other approaches to provide enhancement in extraction.

ELECTROCARDIOGRAM: An electrocardiogram is a picture of the electrical conduction of the heart. By examining changes from normal on the ECG, clinicians can identify a multitude of cardiac disease processes. There are two ways to learn ECG interpretation — pattern recognition (the most common) and understanding the exact electrical vectors recorded by an ECG as they relate to cardiac electrophysiology — and most people learn a combination of both. This tutorial pairs the approaches, as basing ECG interpretation on pattern recognition alone is often not sufficient.

EXISTING METHOD:

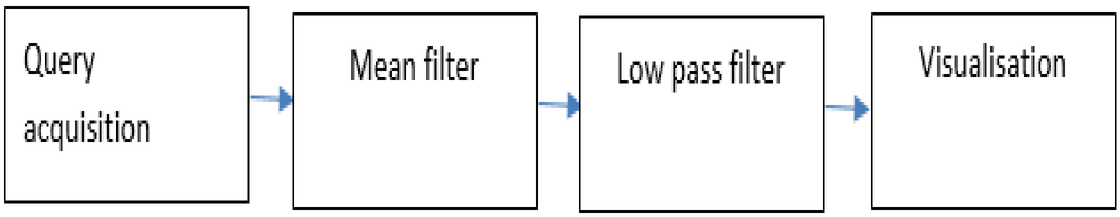


Fig1. Block diagram of the lossless ECG De-noising algorithm

Above block diagram describes the structures of the two filters and their implementation in the XILINX environment. The implementation of the mean filter, Low pass filter using the ISE 14.7 environment using Very high speed integrated circuit Hardware Description Language is presented in this concept.

MEAN FILTER: Mean filter is also known as Box filter and average filter. A mean filter has the following properties.

- It must be odd ordered
- The sum of all the elements should be 1
- All the elements should be same

If we follow this rule, then for a mask of 3x3. We get the following result.

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Since it is a 3x3 mask, that means it has 9 cells. The condition that all the element sum should be equal to 1 can be achieved by dividing each value by 9. As

$1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 = 9/9 = 1$

DIGITAL FIR FILTERS ARCHITECTURE: In signal processing, a finite impulse response (FIR) filter is a filter whose impulse response (or response to any finite length input) is of finite duration, because it settles to zero in finite time. This is in contrast to infinite impulse response (IIR) filters, which may have internal feedback and may continue to respond indefinitely (usually decaying).

The impulse response (that is, the output in response to a Kronecker delta input) of an Nth-order discrete-time FIR filter lasts exactly N + 1 samples (from first nonzero element through last nonzero element) before it then settles to zero.

FIR filters can be discrete-time or continuous-time, and digital or analog.

For a causal discrete-time FIR filter of order N, each value of the output sequence is a weighted sum of the most recent input values:

$$\begin{aligned} y[n] &= b_0 x[n] + b_1 x[n-1] + \cdots + b_N x[n-N] \\ &= \sum_{i=0}^{N} b_i \cdot x[n-i], \end{aligned}$$

where:

- $x[n]$ is the input signal,
- $y[n]$ is the output signal,
- N is the filter order; an Nth-order filter has $(N+1)$ terms on the right-hand side
- b_i is the value of the impulse response at the i'th instant for $0 \leq i \leq N$ of an Nth-order FIR filter. If the filter is a direct form FIR filter then b_i is also a coefficient of the filter .

This computation is also known as discrete convolution.

The $x[n-i]$ in these terms are commonly referred to as taps, based on the structure of a tapped delay line that in many implementations or block diagrams provides the delayed inputs to the multiplication operations. One may speak of a 5th order/6-tap filter, for instance.

NOTCH FILTERING: In signal processing, a **band-stop filter** or **band-rejection filter** is a filter that passes most frequencies unaltered, but attenuates those in a specific range to very low levels.[1] It is the opposite of a band-pass filter. A **notch filter** is a band-stop filter with a narrow stopband (high Q factor).

Narrow notch filters (optical) are used in Raman spectroscopy, live sound reproduction (public address systems, or PA systems) and in instrument amplifiers (especially amplifiers or preamplifiers for acoustic instruments such as acoustic guitar, mandolin, bass instrument amplifier, etc.) to reduce or prevent audio feedback, while having little noticeable effect on the rest of the frequency spectrum (electronic or software filters). Other names include 'band limit filter', 'T-notch filter', 'band-elimination filter', and 'band-reject filter'.

Typically, the width of the stopband is 1 to 2 decades (that is, the highest frequency attenuated is 10 to 100 times the lowest frequency attenuated). However, in the audio band, a notch filter has high and low frequencies that may be only semitones apart.

PROPOSED TECHNIQUE:

Fig:2 Proposed method

FUZZY LOGIC Fuzzy Logic resembles the human decision-making methodology. It deals with vague and imprecise information. This is gross oversimplification of the real-world problems and based on degrees of truth rather than usual true/false or 1/0 like Boolean logic.Take a look at the following diagram. It shows that in fuzzy systems, the values are indicated by a number in the range from 0 to 1. Here 1.0 represents absolute truth and 0.0 represents absolute falseness. The number which indicates the value in fuzzy systems is called the truth value.

PARTICLE SWARM OPTIMIZATION (PSO): PSO is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. The detailed information will be given in following sections. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied. PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far.

FUZZY-BASED PSO PREDICTION METHOD: To improve the accuracy of the prediction technique, particle warm optimisation (PSO) and fuzzy decision techniques were combined into a novel prediction methodology. The principle of the PSO [7] is used for current particles to figure out the optimised solution for future location. The purpose of the PSO is to search a random particle by a defined mathematical formula, which is suitable for one-dimensional signal prediction. Fig shows the four main strategies in the proposed PSO prediction algorithm, in which the prediction of the current value x(t) can be obtained by three passed values x(t −1), x(t −2) and x(t −3). The value of Diff1 is the difference in value between x(t −1) and x(t −2), and Diif2 is the differ- ence in value between x(t −2) and x(t −3). Diff1 and Diff2 can be deter- mined to have a positive or a negative direction of slopes according to the signs of Diff1 and Diff2. The absolution values of Diff1 and Diff2 can be classified into tremendous, large, medium, and small regions according to the correlations with thresholds. The solution space will be obtained by the fuzzy decision rules, as shown in Fig. 1, according to the parameters of difference, direction, and magnitude. Next, a vector V(t) will be the product of an acceleration constant α and a random number β. The PSO uses the results of the fuzzy decision to find the optimal solutions for prediction. The optimal predicted value x’(t) can be estimated approximately by a summation of x(t −1) and V (t). An optimised error rate (e’) can be calculated by the difference between the current value x(t) and the predicted value x’(t). Finally, the optimised error rate (e’) will be sent to the next stage as the predicted difference values for further coding.

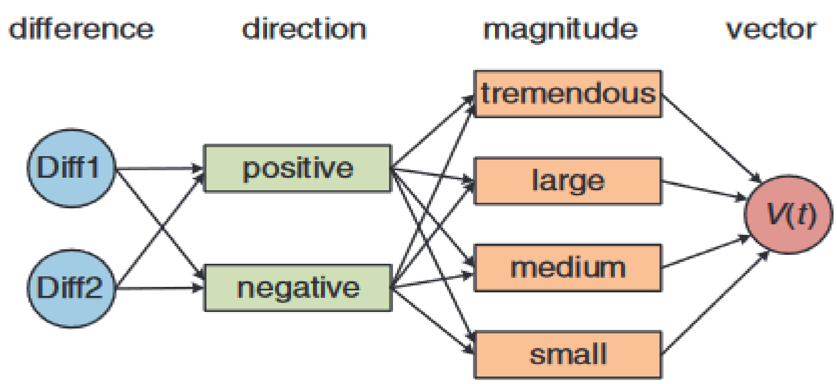


Fig:3 Fuzzy based PSO

equations

$$Diff1 = x(t-1) - x(t-2)$$

$$Diff2 = x(t-2) - x(t-3)$$

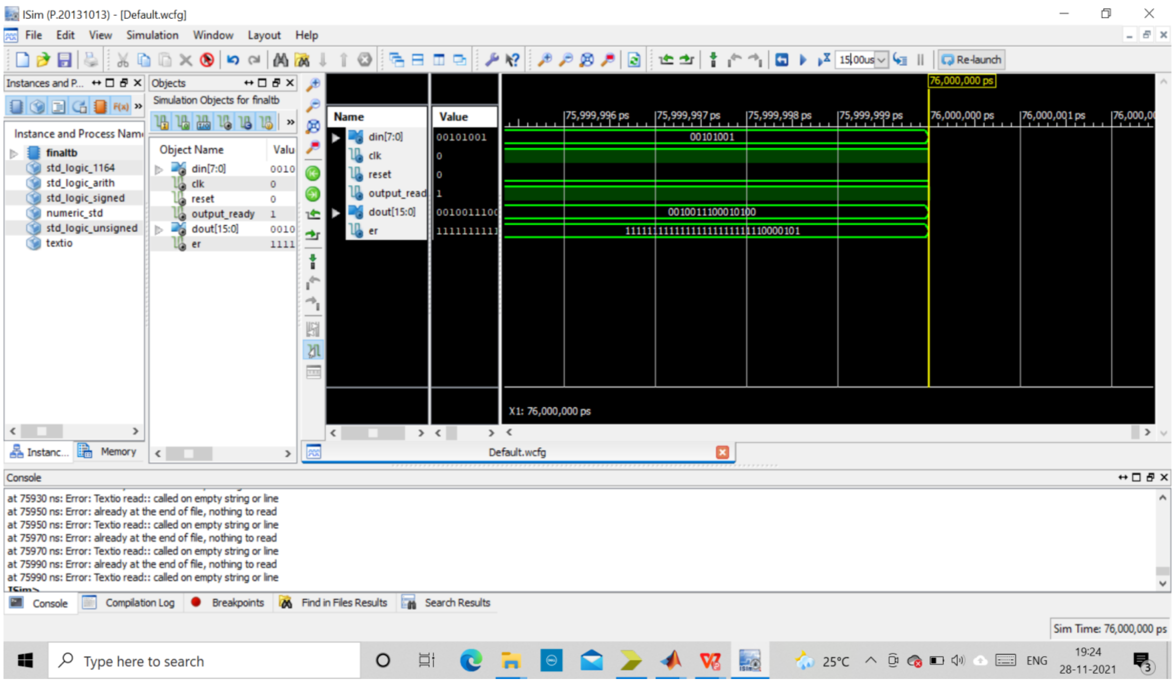
$$V(t) = \alpha \bullet \beta$$

$$x'(t) = x(t-1) + V(t)$$

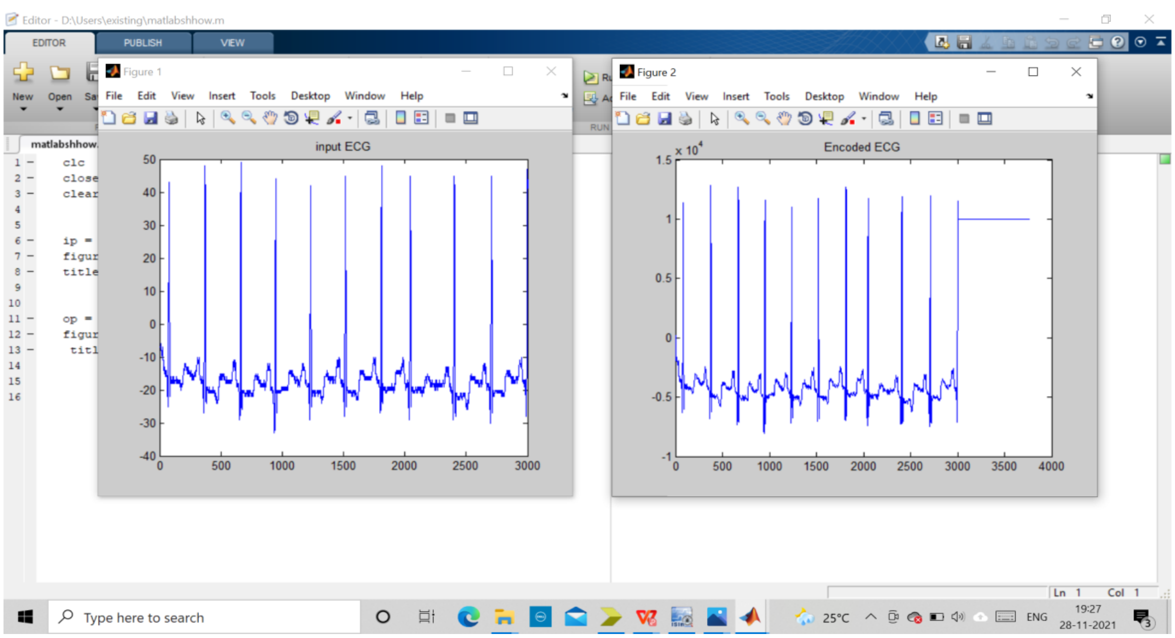
$$e' = [x'(t) - x(t)]$$

This consists of one adder, two subtractors, five registers, and one PSO controller. The value of Diff1 is the difference between the values of x(t −1) and x(t −2), which is the same as Diff2 between x(t −2) and x(t −3). Hence, a hardware sharing technique was used. Compared with the previous design [6], this Letter is successful in replacing a subtractor between x(t −2) and x(t −3) by using a shifter register. In addition, the registers in this design are not only used to store the values of related values but also designed as pipeline registers to improve the performance.

RESULTS:



MATLAB :



ADVANTAGES AND APPLICATIONS:

advantages including minimum signal distortion and low cost. This filter has advantage that this can describe better transformation because this adopts pole and zero both. coefficient compaction, dilution of noise, removal of redundancy Mother Wavelet Filter, lead maximization of coefficient values, best characterization of frequency content Wavelet Thresholding, small wavelet coefficient to zero, retaining or shrinking the coefficients corresponding to desired signal.

Human Body Communication–Based Wearable Technology for Vital Signal Sensing

Natural and Synthetic Sensors

Toward secure and privacy-preserving WIBSN-based health monitoring applications

Cardiovascular Techniques and Technology

Internet of things, smart sensors, and pervasive systems: Enabling connected and pervasive healthcare

CONCLUSION AND FUTURE SCOPE: This paper presents a low power VLSI implementation of the lossless ECG denoising algorithm. The proposed implementation has been tested for different ECG arrhythmia which achieves.The method provides specific advantages due to its applicability to non-stationary and non-linear time series. Perhaps the most difficult problem yet to solve is Also biomedical time series often are recorded over long time spans extending over days and even weeks. This section discusses the scope for further research related to the automated human physiology and emotion detection techniques. The first part of this research investigated the clinical relevance and discriminating ability of fourth-order spectra in the context of cardiac state categorization. A new clinically significant and reduced dimension hybrid feature set of ECG signals has been presented for an accurate and efficient classification of cardiac states using neural network classifier. The developed algorithm is tested and performance has been evaluated using ECG records loaded from the MIT-BIH Arrhythmia database of Physiobank ATM. This research can be extended to test the developed cardiac state classification scheme on real time ECG signals of human subjects instead of standard database signals. The detailed classification accuracy analysis can be performed by configuring different set of classifiers including support vector machines, extreme learning machines and artificial neural network classifiers.

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