LEAST-SQUARE LINEAR PHASE FIR ELECTRO CARDIO GRAPHY (ECG) SIGNAL ANALYSIS

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ABSTRACT
Signal processing methodology to analyze Electrocardiography (ECG) signals is proposed in this paper. Discrete Wavelet Transform (DWT) is employed as a feature extraction tool to achieve efficient design, and to overcome the limitations of previous methodologies like Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT). Least-Square Linear Phase FIR filtering denoising methodology is presented in this design to suppress baseline wander noise. Feed forward neural network methodology is used as the classifier to analyze the ECG signal from the myocardium. The proposed design is implemented on FPGA with low resources utilization, and achieving overall accuracy of 97.78% for classifying ECG signals.

KEYWORDS: *Electro Cardio Graphy (ECG), Discrete Wavelet Transform (DWT), DSP and Bio-Medical Applications.*

I. INTRODUCTION

The ECG analysis is based on recording the heart's electrical activity. Any variation in normal ECG signal patterns which are known as heart beats arrhythmia are diagnosed as defect in heart muscle functions. Cardiac cells are electrically polarized in normal state. The inner sides of cardiac cells are negatively charged with respect to their outer sides. The main electrical activity of the heart comes from the depolarization process, the process in which the cardiac cells lose their normal negativity. This process propagates through cardiac cells generating electric current that can be sensed by the electrodes mounted on the body surface. Once this depolarization process is completed, the cardiac cells restore back their normal polarity by a process called re-polarization [1].

Previous methodologies for analyzing of ECG signals are based on time domain methods. These methodologies are not always perfect to study all the properties of the ECG signals. To overcome this shortage, Fast Fourier Transform (FTT) is applied to study the frequency spectrum of the ECG signal [2, 3]. This methodology has its own limitation due to its inability to determine the location of the frequency components with respect to time. Short Term Fourier Transform (STFT) has been used to overcome this issue [4].The major draw-back of STFT is its non-optimum time frequency precision.

The wavelet transform emerges as a tool that is used to solve the above issue [5, 6, 7 and 8]. Wavelet transform depends on set of analyzing wavelets allowing the decomposition of ECG signal into a set of coefficients. Each analyzing wavelet has its own time duration, time location and frequency band. The wavelet coefficients resulting from this decomposition correspond to a measurement of the ECG components in this time segment and frequency band.

In this paper Least-Square Linear Phase FIR ECG (LLFE) to analyze ECG is presented. LLFE employs the discrete wavelet transform methodology to overcome the limitations of the previous methodologies while time domain analysis is unable to determine the location of the frequency components with respect to time and STFT has the disadvantage of non-optimum time frequency precision when analyzing ECG signals.

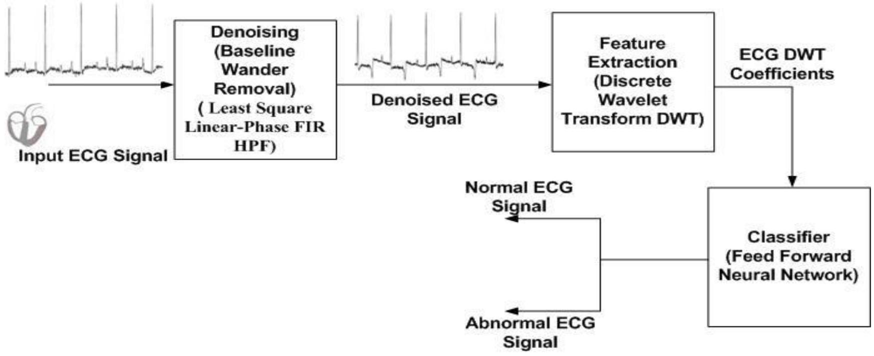

Figure 1. LLFE design block diagram

LLFE employs the Least-Square FIR filtering as a methodology to remove low frequency noise which is embedded in the ECG signals.

The paper is organized as follows. The proposed design block diagram along with the function of each block are discussed in section II. In section III, the design implementation technique is presented. Simulation results are provided in section IV. The conclusions are summarized in section V. Targeted future work is demonstrated in section VI.

II. LLFE DESIGN

The block diagram of the proposed design is shown in Figure 1. The block diagram consists of three main blocks: Denoising block, Feature Extraction block and Classifier block. Different blocks are described in the following subsections.

2.1. Denoising Block

ECG signals suffer from two types of noise: (1) Low frequency noise represented in baseline wander noise, (2) High frequency noise such as power-line interference noise and muscle contraction [9]. In LLFE, high frequency noise is removed by discarding the first detail component resulting from wavelet transform decomposition. The low frequency noise is represented by baseline wandering noise. In wandering baseline, the isoelectric line changes position. Primary possible causes for baseline wandering noise are the cables moving during reading, patient movement, dirty lead wires/electrodes, loose electrodes, in addition to other minor sources.

The baseline wander noise makes it difficult to analyze ECG signals, it is necessary to remove this type of noise for correct analysis of ECG signals. Baseline wandering noise is removed in LLFE design using Least-Square Linear Phase FIR high-pass filtering. An example of ECG signal suffering from baseline wander noise before and after denoising using LLFE high-pass filtering method is shown in Figures 2 and 3, respectively. The isoelectric line is almost flat in Figure 3 after noise removal.

2.2. Feature Extraction

Wavelet transform has a filter structure as shown in Figure 4. DWT uses filter bank methodology to separate low frequency and high frequency from original source [10]. The input signal is filtered by the low-pass (LP) and the high-pass (HP) filters. The outputs from the low-pass filter are called the approximation coefficients while the outputs from the high-pass filter are called the detail coefficients. The output of each filter is then down sampled by a factor of 2. The LP filter output is further filtered and this process goes on until enough steps of decomposition are reached. In LLFE the input signal is passed through three levels of filtering results in four signals (d1, d2, d3 and a3).

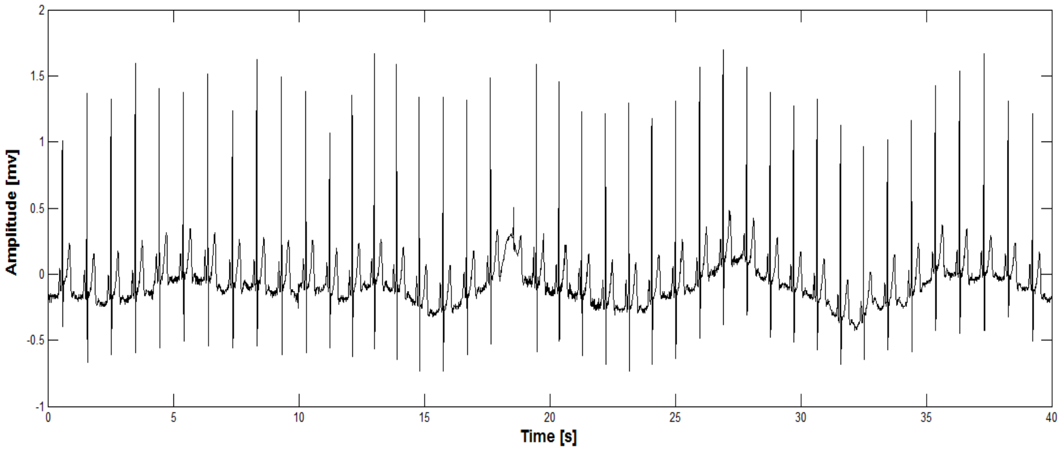

Figure 2.ECG signal suffers from baseline wander.

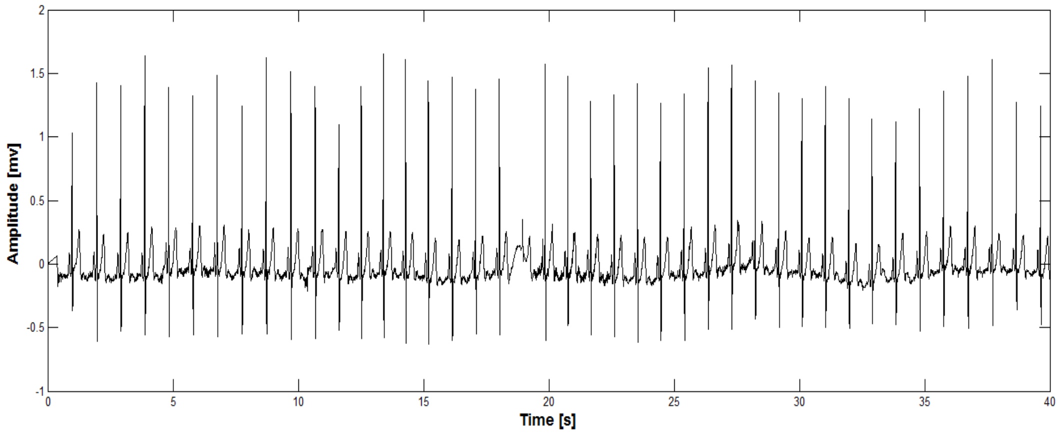

Figure 3.ECG after baseline wander removal using LLFE.

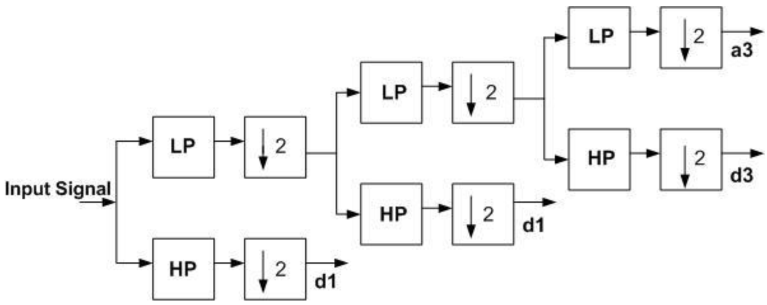

Figure 4. Wavelet Transform Filter Structure Block Diagram.

The Feature extraction is done by wavelet transform decomposition. In this step, the continuous ECG signals are transformed into individual ECG beats. The width of individual beats is approximated to 300 sample data, and the extracted beat is centred around R peak. The annotation provided by the database is used to do the transformation. The R peak annotation is used as the pivot point for each beat.

For each R-peak, the continuous signal for each beat start at R-150 position is cutoff until R+149 position therefore a beat with 300 sample data in width is achieved [5].

In this decomposition, Daubechies order 3 is used as a mother wavelet. In this method the input signal is decomposed into 3 levels as shown in Figure 4. The input signal with 300 samples will be down sampled by a factor of 2 in each stage, reaching only 38 samples in the 3rd stage (d3, a3).The detail d1 is usually noise signal and has to be eliminated. (d2) and (d3) represent the high frequency coefficients of the signal. Since (a3) represents the approximation of the signal, it contains the main feature of the signal, thus (a3) is used as reduced feature vector that is used in the subsequent stage for the classifier.

In LLFE design, the Wavelet Transform block is implemented using the direct filter bank methodology. LLFE design depends on classifying normal ECG beats and abnormal beats. The processed ECG signal samples are extracted from MIT-BIH Arrhythmia Database. In Table 1, normal/abnormal ECG beats based on MIT-BIH database that is considered is classified, those beats are considered to be processed using the wavelet transform block. Each signal in the table is referenced from the MIT-BIH database by selecting the target database (MIT-BIH Arrhythmia Database (MITDB)) that contains the selected records digitized with sampling frequency 360 Hz.

2.3. Classification Block

Some designs use neural network as their classifier in classifying ECG signals [11, 12, and 13]. The classifier which is implemented in LLFE is based on feed forward neural network; the neural network output indicates whether the sample provided in the input of the design represents normal beat or abnormal beat. The output y of each neuron of the neural network according to the input x and neurons weights w and bias b and activation function g is shown below in (1) [14],

$$y=g\left(\sum_i x_i w_i + b\right) \quad (1)$$

The basic blocks of the neural network are: multiplier block, adder block and the activation function block. The neural network in this design has one hidden layer with 4 hidden neurons and 1 output neuron. The activation function used in LLFE is (tansig) activation function. The (tansig) activation function can be expressed in exponential form by (2) [15],

$$tansig(x)=2/(1+e^{-2x}) - 1 \quad (2)$$

From (2), this exponential form can be expressed in form of Maclaurin power series approximated to x to the power 5 as in (3),

$$tansig(x) = x - x^3/3 + 2x^5/15 \quad (3)$$

The neural network passes through 2 phases: Training Phase and Testing Phase. In Training Phase 90 training sets, with 48 normal ECG sets and 42 abnormal ECG sets (each set is divided to 38 samples, (a3), output from the wavelet transform block) are used. Testing phase is used to validate the functionality of the implemented neural network. Total 45 testing sets with 24 normal beats and 21 abnormal beats are used.

III. LLFE IMPLEMENTATION

The complete design is assembled and tested. The proposed design is implemented on FPGA using XILINX Spartan-3A DSP XC3SD3400A board. In [5] the design is implemented using XILINX Spartan 3AN-XC3S700AN. Table 2 indicates the device utilization comparison with LLFE. In [5] device utilization is presented in percentage form, this percentage is translated here to the actual number of logic resources. This translation is done to make fair comparison as LLFE and [5] are implemented on two different boards.

Table 1. MIT-BIH DB records categorization according to normality/abnormality [6].

Class	Record Number
Normal (24)	100-101-103-105-106-112-113-114-115-116-117-121-122-123-201-202-205-209-213-215-219-220-222-234
Abnormal (21)	104-108-109-111-118-119-124-200-203-207-208-210-212-214-217-221-223-228-230-231-232

Table 2. Device utilization summary.

Logic Utilization	Utilization	
	LLFE	[5]
Number of Slice Flip Flops	3893	7301
Number of 4 input LUTs	3953	7654
Total Number of 4 input LUTs	4321	8832
Number of bonded IOBs	140	14
Number of BUFGMUXs	4	4

Table 3. Confusion Matrix of the neural network classifier.

	Classes classification		
Number of inputs	**Normal Class**	**Abnormal Class**	**Accuracy (%)**
Normal Class (24)	24	0	100
Abnormal Class (21)	1	20	95.23

From Table 2, it is shown that the LLFE achieves reduction in resources utilized on FPGA implementation compared to [5].

IV. SIMULATION RESULTS

LLFE is tested to assess the accuracy of the circuit. As mentioned in section 2.3, LLFE uses 45 testing sets with 24 normal beats and 21 abnormal beats. The simulation is started by getting the denoised ECG beat output from the denoising stage (300 samples data), and input this denoised beat to the feature extraction DWT stage, the output of the DWT stage which is (a3), 38 samples feature vector, is input to the classifier stage, the neural network output layer contains only one output neuron. The output of the neural network is measured for each tested ECG beat indicating whether the ECG beat under test is classified as normal or abnormal beat, then this neural network output is examined against whether this classification correctly classifies the input test beat or not.

In Table 3, examination of classification (confusion matrix) indicates that all normal ECG test beats are diagnosed correctly as normal beats, while only one abnormal test beat out of 21 abnormal test beats is identified incorrectly as a normal beat, giving that the accuracy of identifying the normal ECG beats is 100%, while the accuracy of identifying abnormal ECG beats is 95.23%. The total accuracy of LLFE is 97.78%.

The accuracy in [5] ranges from 90% to 100%. In [6] the same accuracy 97.8% is achieved. However, in [6] the design is not implemented on a hardware platform, so, it is hard to assess its hardware utilization efficiency compared to LLFE. From this comparison it is shown that LLFE has a good accuracy in analyzing ECG signals.

V. CONCLUSIONS

In this paper, Least-Square Linear Phase FIR (LLFE) design for analyzing ECG signals is proposed. LLFE employs Least-Square Linear Phase FIR high-pass filtering as a denoising methodology to remove baseline wander noise from the input ECG signal. LLFE employs Discrete Wavelet Transform as a feature extraction methodology to extract the main features from the denoised ECG signal. The proposed design depends on the classification of the approximate wavelet transform coefficients at level-3 using feed forward neural network to identify the normality or the abnormality of the ECG signal. LLFE achieves accuracy of 100% in identifying normal ECG beats, and accuracy of 95.23% in identifying abnormal ECG beats, achieving overall accuracy of 97.78% in analyzing ECG signals. The design is implemented on FPGA using XILINX Spartan-3A DSP XC3SD3400A board, achieving low resources utilization.

VI. FUTURE WORK

The proposed design is implemented on FPGA as presented in this paper, however, LLFE design is targeted to be implemented on ASIC to achieve high performance, low power consumption, and high level of integration, enabling LLFE to be portable and handy, and also in lower cost

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