ASIC Implementation of an Adaptive Noise Canceller for ECG Signal Processing Applications

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Abstract- *Electrocardiogram (ECG), a noninvasive technique is used as a primary diagnostic tool for cardiovascular diseases. A cleaned ECG signal provides necessary information about the electrophysiology of the heart diseases. It provides valuable information about the functional aspects of the heart and cardiovascular system. The objective is to automatic detection of cardiac arrhythmias in ECG signal. This work focuses on developing a sophisticated, small and reliable ASIC (Application Specific Integrated Circuit) chip that can be used for monitoring and detecting the rate of heart beat for heart transplantation patient. Well known adaptive noise cancellation techniques are such as LMS (Least Mean Square) and RLS (Recursive Least Mean Square) have been extensively used for noise cancellation techniques with good performance. The proposed architectures have been modeled and verified for their functionality. Using the entire ASIC flow, suitable results obtained at various stages are compared and reported. The high computational requirement of all adaptive filtering algorithms has limited the scope of its use in medical applications. However, with rapid advances in VLSI (Very Large Scale Integration) technology, it is possible to implement complex circuits in a single chip. This work focuses on developing architectures for adaptive noise cancellation and its ASIC implementation.*

Keywords- Heart rate variability (HRV), Adaptive filter, Fast Fourier transform (FFT), Electrocardiogram (ECG)

I. INTRODUCTION

There is an enormous demand for reducing size and power of transferable devices, used for monitoring critical signals such as electrocardiogram (ECG), electroencephalogram (EEG) and electromyogram (EMG). Besides biomedical products, there are large number of emerging healthcare applications that involve sensors and their associated precise instrumentation and signal conditioning. Low power, miniaturized and low cost monitoring/sensing devices are the key components in such systems. The performance of these devices directly depends on analog signal conditioning, which must extract and amplify extremely small signals from a noisy environment. Myopotential spectrum is predominant at higher frequencies and significantly overlaps with the spectrum of the ECG signal, primarily with the spectrum of the QRS complex [1]. Thus, the automatic interpretation, following accurate detection of characteristic ECG points and waves, and measurement of signal parameters, become difficult. EMG noise is caused by increased muscle activity. The ECG signal is used to know the cardiac condition of an ambulatory patient. Wireless Ambulatory ECG recording is now routinely used to detect arrhythmias and cardiac abnormalities. As the ECG signal contains numerous artifacts, these artifacts have to be removed before monitoring, from the receiver point-of-view, so that a correct decision can be taken. So, it is necessary to remove the different artifacts present in the ECG signal hence there is a need of filtering the ECG signal. In a practical case most of the signals are nonstationary and the filter, which we use must change its coefficient according to the input signal. Several filtering techniques have been presented in literature for ECG analysis, which includes, adaptive and non adaptive techniques [11]–[13], adaptive filtering techniques permit to the detect time varying potentials and to track the dynamic variations of the signals.

Electrical activity of heart can be recorded with surface electrodes on chest or limbs. ECG wave shape may be altered by cardiovascular diseases, atrial fibrillation, and ventricular fibrillation and conduction problems. ECG signal comprises of P wave, PG segment, QRS complex, ST segment and T wave. QRS complex wave shape is affected by conduction disorders. Ventricular enlargement could cause a wider than normal QRS complex. The ST segment may be depressed due to myocardial infarction. Presence of noise is one of the most challenging problems in Signal Processing basically due to the fact that a signal can pick up noise and be distorted such that the information carried by the signal can be misinterpreted. Thus, it is important that the impairments due to noise is reduced or eliminated totally from signals in almost all signal processing and communications tasks. Filtering is widely used to remove the noise from the signal. However, in the process, it also removes a part of the signal, which may be an important part of the signal processing application.

The wavelet transform is an emerging signal processing technique that can be used to represent real-life non stationary signals with high efficiency [1]. Indeed, the wavelet transform is gaining momentum to become an alternative tool to traditional time-frequency representation techniques such as the discrete Fourier transform and the discrete cosine transform. By virtue of its multi-resolution representation capability, the wavelet transform has been used effectively in vital applications such as transient signal analysis [2], numerical analysis [3], computer vision [4], and image compression [5], among many other audiovisual applications. Wavelet transform is mostly needed to be embedded in consumer electronics, and thus a single chip hardware implementation is more desirable than a multi-chip parallel system implementation. However, time-varying autoregressive models allow assessing, on a beat to beat basis, the spectral parameters of HRV signal in a fast and efficient way independently on the transitory events found through the whole night recording (provoked by arousals, body movements, and changes on sleep stages or apneas).

In the last few decades the demand for portable and embedded digital signal processing (DSP) systems has increased dramatically. Applications such as cell phones, hearing aids, and digital audio devices are applications with stringent constraints such as area, speed and power consumption. These applications require an implementation that meets these constraints with the shortest time to market. The possible alternative implementations that can be used range from an ASIC custom chip, general purpose processor (GPP) to DSP processors. While the first choice could provide the solution that meets all the hard constraints, it lacks the flexibility that exists in the other two, and also its design cycle is much longer. FPGAs prove particularly useful in data path designs, where the regular structure of the array can be utilized effectively. The programmability of FPGAs adds flexibility not available in custom approaches, while retaining relatively high system clock rates.

II. RELATED WORK AND ISSUES

The nonlinear filter that uses reversible WT allows estimating noise level in individual decomposition bands and proportionally adapting correction of WT coefficients. In this way, we can achieve effective noise suppression while distortion of the ECG signal is minimized. Besides the choice of decomposition and reconstruction filter banks, the choice of the level of decomposition and the strategy of WT coefficient adjustment are also important. Different strategies of thresholding the WT coefficients with down sampling are discussed in [4]. In [5], the author attempts to optimize the threshold parameters for a wavelet filter with WT with decimation, and concludes that the optimal parameter values depend on the level of interference. The disadvantage of filtering with WT with down sampling is that the result is dependent on the choice of the beginning of the filtering and the need for interpolation in reverse transform, which is always a source of errors. Transform without down sampling, the so called stationary (redundant) wavelet transform (SWT), is more preferable for filtering. Thresholding using SWT is solved in [6]. Better results can be achieved by using the wavelet Wiener filtering, when each transform coefficient is adjusted separately. The Wiener filter requires an estimate of a noise-free signal, which is necessary to calculate the correction factor for the adjustment of transform coefficients. The principle of the method was described in [7], where the estimate of the noise-free signal was performed using another wavelet filter, both implemented with decimation. The wavelet Wiener filtering (WWF) with decimation and with simplified estimation of the noise-free signal was used in [2]. In [8], SWT with estimation of the noise-free signal was used. The estimation was carried out with WT with decimation and hard thresholding. In [9], both the transforms are stationary; the estimation of a noise-free signal was carried out by nonnegative garrote thresholding. The filters were tested on signals with artificial noise, whose power spectrum was adapted to the spectrum of an EMG signal. The parameters of all the Wiener filters mentioned were set intuitively. The authors of all the papers cited used dyadic transforms.

A flowchart demonstrating the signal processing steps of the Pan and Tompkins algorithm (Pan & Tompkins, 1985) for the classical derivative-based QRS detection is shown in Fig. 3. The ECG signal first passes through a set of linear processes, including a band-pass filter comprising a cascaded low-pass and high-pass, and a derivative function. Non-linear transformation is then employed in form of a signal amplitude squaring function. Finally, moving window integration is performed before an adaptive threshold is applied for detection of the QRS complexes. The underlining principle of the algorithm is the detection of the slope of the R wave through the derivative function, amplified by the squaring function. The moving-window integration then provides wave-form feature information in addition to the detected R wave slope. Different from conventional method, in our system, as we are only interested in the RR interval in HRV analysis, we choose to assign an R peak to each detected R slope from the output of the squaring function through an adaptive threshold. Thus, we only require the band-pass filter, derivative function, squaring function, and adaptive threshold in our system. After differentiation, squaring function is employed to enhance the characteristics of the signal. Then a threshold is applied to the squared signal to detect the start of the QRS complex. The peak of the squared signal is identified as the R peak of the ECG data.

III. ADAPTIVE NOISE CANCELLER

During digital signal processing, a number of unpredictable signals, noises or time-varying signals often need to process, it is impossible to achieve optimal filtering for fixed coefficient filter, so adaptive noise canceller must be designed to track the change of signal and noise. Adaptive noise canceller consists of two basic parts: the filter which applies the required processing on the incoming signal which is to be filtered, and an adaptive algorithm, which adjusts the coefficients of that filter to somehow improve its performance. When adaptive noise canceller is designed, the autocorrelation function of signals and noises cannot be known in advance. During the filtering, with the autocorrelation function of signals and noises changing slowly over time, filter can automatically adapt and adjust to meet the requirements of the minimum mean squared error.

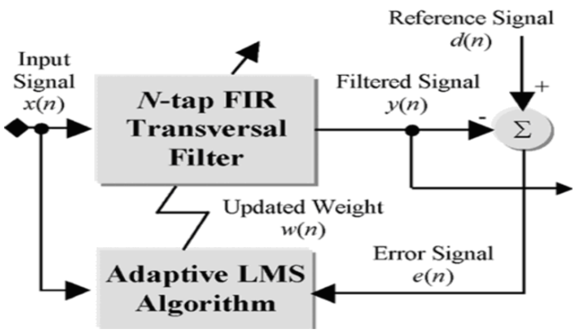

Figure 1. Simplified Adaptive Noise Canceller

Fig.1 shows the structure of adaptive filter. The objective is to filter the input signal, x(n), with an adaptive filter in such a manner that it matches the desired signal, d(n). The desired signal, d(n), is subtracted from the filtered signal, y(n), to generate an error signal, e(n).

The LMS algorithm is a widely used technique for adaptive filtering. A significant feature of the LMS algorithm is simplicity. In this algorithm filter weights are updated with each new sample as required to meet the desired output. The computation required for weights update is illustrated by equation. If the input values x(n), x(n-1), x(n-2)……… x(n-N+1) form the tap input vector x(n) where N denotes the filter length, and the weights w (n),w1(n),w2(n) ……. form the tap weight vector w(n), then the LMS algorithm is given by the following equations:

$$y(n) = wH(n)\ u(n)$$

$$e(n) = d(n) - y(n)$$

$$w(n + 1) = w(n) + \mu\ u(n)e(n)$$

y(n) denotes the filter output, d(n) denotes the desired output, e(n) denotes the filter error (the difference between the desired filter output and current filter output) which is used to update the TAP weights, μ denotes a learning rate, and bw(n+1) denotes the new weight vector that will be used by the next iteration. A computationally simpler version of the gradient search method is the least mean square (LMS) filter, in which the gradient of the mean square error is substituted with the gradient of the instantaneous squared error function.

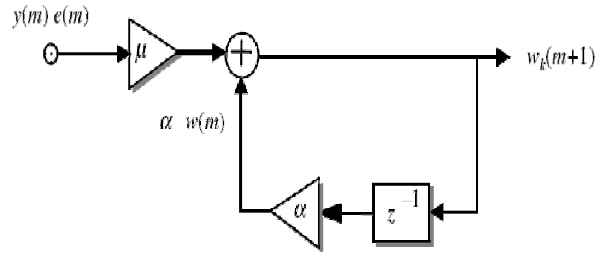

Figure 2. LMS Equation Implementation

A normal FIR filter based on MAC operations could be used to implement this algorithm. A weight update mechanism should be added to the FIR filter to update the filter weights according to the calculated error. This module requires extra multiplications and additions.

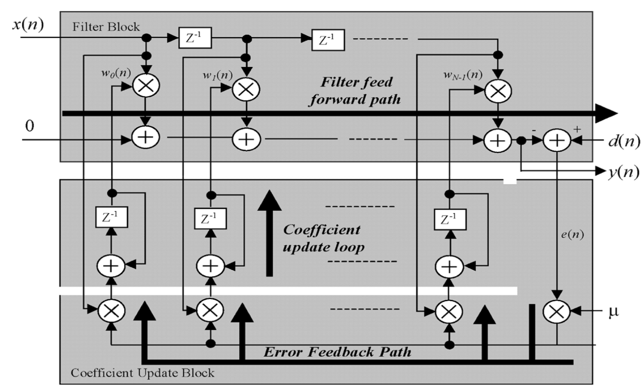

Figure 3. FIR-LMS Filter Structure

The filter outputs obtained from the FIR block are used by the LMS algorithm to calculate the changes to the filter coefficients, Δh, required for the next filtering process. When echo data is received from the link it is buffered and upon subtraction from the filter output values, the error term e(n) is obtained. This is used for obtaining the Δh values to be added/subtracted from the current filter coefficients. Once the new coefficients are available, an h available flag is asserted informing the FIR block that the new coefficients are available for the next filtering process to initiate. This process is repeated until the error term fed into the system is negligible. The most critical part in the design of the LMS block is the learning factor whose optimum value had to be found by trial and error within the bounds specified by the algorithm. The learning factor determines how fast the algorithm converges. Setting a learning factor that is too large results in the output oscillating due to overshoot, hence convergence is never reached. On the other hand, if the learning factor is too small slow convergence speeds will result, hence increasing the risk of overflow in the input buffers.

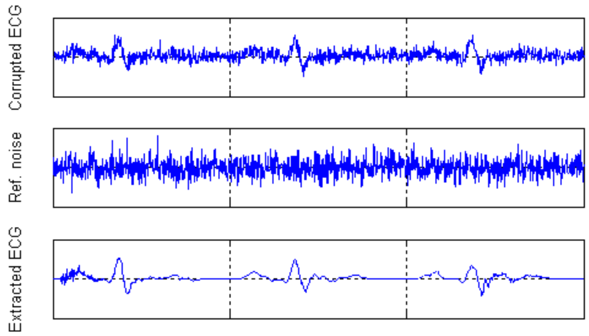

Figure 4. ECG Signal Processing

The Least Mean Square (LMS) algorithm was first developed by Widrow and Hoff in 1959. It has become one of the most widely used algorithms in adaptive filtering. The LMS algorithm is a type of adaptive filter known as stochastic gradient-based algorithms as it utilizes the gradient vector of the filter tap weights to converge on the optimal wiener solution (Mahesh Godavarti 2005). It is well known and widely used due to its computational simplicity. It is this simplicity that has made it the benchmark against which all other adaptive filtering algorithms are judged as said by Sinead Mullins and Conor Heneghan (2002).

IV. EXPERIMENTAL RESULTS

The ECG signals used in our testing are from the standard physionet database. This database consists of two sets of 125 realistic 12-lead and 3-lead (orthogonal) ECG signals. Electrocardiograms have a length of 10 s and were sampled at 500 Hz sampling frequency with a quantization step of 5 μV. The signals contain interference, whose SNR is between 0 and 50 dB, although some segments of the signals can contain noise ranging from −5 to 55 dB. The artificial noise used for testing was generated individually for each signal, respecting the original noise level and its time dependence. If we filter the whole database using our proposed technique, the SNR increases for all signals.

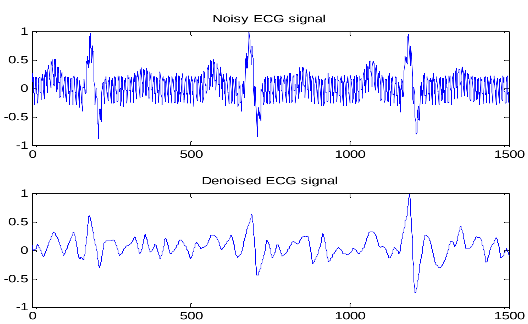

Figure 5. Denoised ECG Signal Using Adaptive Filter

In this section, providing adequate healthcare for the gradually aging population, in light of reduced personnel and rising costs, is a problem the modern world that is currently faced with. Portable medical systems developed for bringing healthcare to the average user as well as the elderly is a rising trend which can benefit the entire social healthcare infrastructure. To enable practical employment of ever-present healthcare devices for portable medical applications, an experimental ECG system-on-chip prototype has been developed. Here we describe the architecture of the proposed ECG SOC as well as the means of system verification including a Xilinx FPGA, which are connected to the ARM processor through an AMBA High-performance Bus (AHB). The designed HRV processer is implemented on the FPGA and verified with patterns sent from a PC. In-circuit emulator (ICE) is employed to feed ECG patterns into the ARM processor which then passed the data to the FPGA on the AHB bus. To connect the HRV processor on the FPGA to the AHB bus, an AHB wrapper is added to the original architecture, which provides a handshaking interface between the HRV processor and the AHB bus. The UART module is also implemented so that the capability to communicate with the Bluetooth module using a system clock of 24 MHz could be verified. The Modelsim simulation for FPGA verification is shown in Fig.10. Tests using the Socle Development Platform have verified that the HRV processor is capable of calculating time–frequency analysis in real-time and is possible to implement using VLSI technology.

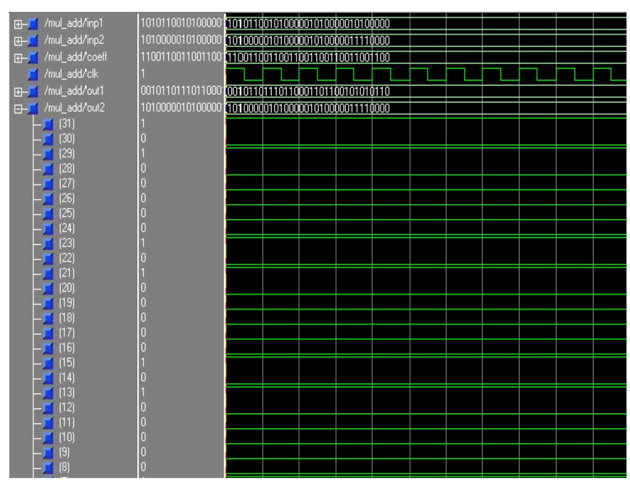

Figure 6. HDL Simulation Output

V. CONCLUSION

Adaptive noise cancellation technique is proposed to remove power line interference from ECG signal using ASIC technology. Performance optimization is obtained through pipelining and resource-sharing techniques. It focuses on very-large-scale integration (VLSI) architecture and application-specific integrated circuit of a robust algorithm for removing power line interference in multichannel biopotential recording. When compared with three similar interference removal methods, the proposed algorithm outperforms in terms of robustness and interference rejection performance.

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