ASIC CHIP DESIGN FOR HEART RATE MONITORING AND SIGNAL PROCESSING

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Abstract – The objective of heart rate monitoring and processing devices is to perform automatic detection of cardiac arrhythmias in ECG signal. This work focuses on developing a sophisticated, small and reliable ASIC chip that can be used for monitoring and detecting the rate of heart beat for heart transplantation patient. Noise removal in heart rate signal is carried out by well known adaptive noise cancellation techniques such as LMS and RLS algorithms. In this work, ASIC chip is designed for heart rate monitoring and signal processing is done using LMS based adaptive algorithm. 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 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.

Index Terms- Application Specific Integrated Circuit, Heart rate variability (HRV), Adaptive filter, Electrocardiogram (ECG)

I. INTRODUCTION

Portable devices have gained a huge attention recently 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, 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
tries 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.

In classical derivative-based QRS detection, 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 such as 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

Figure 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:

\[ y(n) = w^H(n) u(n) \]
\[ e(n) = d(n) - y(n) \]
\[ w(n + 1) = w(n) + \mu u(n)e(n) \]

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, \( \mu \) 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 depicts the implementation of LMS equation using basic blocks.

The filter outputs obtained from the FIR block are used by the LMS algorithm to calculate the changes to the filter coefficients, 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 \( \Delta h \) 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.

The Least Mean Square (LMS) algorithm was first developed by Widrow and Hoff. 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 4. Denoised ECG Signal Using Adaptive Filter

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 processor 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 Figure 5 and layout is given in Figure 6. 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 5. HDL Simulation Output

Figure 6. Layout of the designed chip

V. CONCLUSION

In this work, ASIC chip is designed for heart rate monitoring and signal processing is done using LMS based adaptive algorithm. 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 technology, it is possible to implement complex circuits in a single chip. Heart rate monitoring and processing chip is developed and the simulation and implementation results are obtained.
REFERENCES


