Embedded MCSoC Architecture and Period-Peak Detection (PPD) Algorithm for ECG/EKG Processing

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Abstract: Electrocardiography (ECG/EKG) is an interpretation of the electrical activity of the heart over time captured and externally recorded by electrodes. It is an essential practice in heart medicine, which faces computational challenges, especially with 12 lead signals or more. This paper exploits parallel processing techniques to process electrocardiography computation kernels in parallel and under different sampling frequencies. This work is part of a project named BANSMOM project\textsuperscript{a}. We present a novel Period-Peak Detection (PPD) algorithm for heart signals processing via the use of a novel embedded MCSoC architecture. The ECG/EKG algorithm and the system architecture are presented in a fair amount of details.

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1 Introduction

With heart diseases, and associated complications being one of the main causes of death around the world, and in spite of decreases mortality rate, detection of irregularities in the rhythms of the heart is a growing concern in medical research. Embedded health monitoring system is an approach to deal with such problem. However, design of such systems face a number of challenging tasks, since they need to address often conflicting requirements for performance, size, and precision. In addition, existing methods use wearable systems, which are not flexible and not easy to use. Accuracy of these systems is also questioned.

In health monitoring applications, a wide range of parameters must be available, processed and combined and multiple tasks must be performed in order to obtain an accurate diagnosis. In most cases, complex computation is required because of the detection algorithm applied. When real time diagnosis need to be done, especially for portable systems, a single low power, medium performance processor might have problems to deal with all tasks.

Traditionally, personal medical monitoring systems, such as Holter monitors, have been used only to collect data. Data processing and analysis are performed off line, making such devices impractical for continual monitoring and early detection of medical disorders. Moreover, systems with multiple sensors for physical rehabilitation often feature unwieldy wires between the sensors and the monitoring system. These wires may limit the patient’s activity and level of comfort and thus negatively influence the measured results \cite{1}. In addition, individual sensors often operate as stand-alone systems and usually do not offer flexibility and integration with third-party devices. Therefore, the need for a new health monitoring systems is imperative.

Systems on chip are becoming a common design alternative in portable systems due to the possibility to manufacture a silicon chip including only the necessary elements \cite{2}. Certain medical applications require devices capable to provide accurate information about the monitored patient in places where a complex clinical system is not available, and parameters such as electrocardiogram (ECG/EKG) characteristics are important to be determined \cite{2}.

ECG/EKG is an essential practice in heart medicine, which faces computational challenges, especially when 12 lead signals are to be analyzed in parallel, in real time, and under increasing sampling frequencies. Another challenge is the analysis of huge amount of data that may grow to days of recording. Our solution is to use a network on chip based parallel processor to process ECG/EKG computation kernels in parallel. Our system uses small number of tinny wireless in-body sensors (embedded in human body) to create a real wireless in-body area network that can be used to monitor elderly people health status, and providing real-time feedback to the user and medical personnel.

We earlier researched about a low power, low complexity processor targeted for ubiquitous computing and based on a novel queue computing model. We also researched about several synthesis and mapping algorithms targeting ubiquitous applications.

This paper proposes a novel algorithm for ECG/EKG human heart signals analysis via the use of multicore architecture instead of conventional techniques which lack accuracy and scalability. We describe the system hardware architecture in fair amount of details. Our final ultimate goal is to allow continuous streaming, real-time, analysis and display and concurrent transmission of the
final signals to the hospital. The present work is a part of whole project named BANSMOM - Smart Monitoring System for Future Social Information Infrastructure [3].

The rest of the paper is organized as follows: Section two presents related work. Section three presents new ECG/EKG algorithm. Section four presents the system architecture. Section five presents the system design methodology and sample design. The last section presents concluding remarks and future work.

2 Related Work

A number of recent research efforts focus on wearable systems for health monitoring. Researchers at the MIT Media Lab have developed MIThril, a wearable computing platform compatible with both custom and off-the-shelf sensors. The MIThril includes ECG/EKG, skin temperature, and galvanic skin response (GSR) sensors. In addition, they demonstrated step and gait analysis using 3-axis accelerometers, rate gyro, and pressure sensors [4]. MIThril is being used to research human behavior recognition and to create context-aware computing interfaces [5]. Rosado [2] implemented a DSP correlation algorithm for ECG/EKG on a programmable logic as support for a main processor, with direct input from analog-to-digital converter (ADC), and interface with the main processor, which control the implemented algorithm.

CodeBlue, a Harvard University research project, is also focused on developing wireless sensor networks for medical applications. They have developed wireless pulse oximeter sensors, wireless ECG/EKG sensors, and triaxial accelerometer motion sensors. The sensors, when outfitted on patients in hospitals, use the ad-hoc networks to transmit vital signs to health care centers [6, 7].

Another work is done by Otto in [8]. He describes a general WBAN architecture and how it can be integrated into a broader telemedical system. The WBAN includes several motion sensors that monitor the user overall activity and an ECG/EKG sensor for monitoring heart activity.

Recent technique deployed for monitoring heart activity is the 12-lead ECG, which makes use of data coming from twelve ECG leads serially. The leads produce huge amounts of data especially when used for a long number of hours. Figure 1 shows an example of a typical ECG/EKG signal. The most important points on the ECG/EKG signal is the peaks: P, Q, R, S, T, and U. Each peak is related to a heart action that is of importance to the medical analysis.

Many ECG/EKG analysis methods use the three peaks Q, R, S and the corresponding intervals between these three peaks. This interval from Q to R to S is known in biomedical terms as the QRS complex. The well known QRS Pan-Tompkins algorithm locates R-peaks in the ECG/EKG signal and calculates the heart period [9].

3 PPD Algorithm

Our Period-Peaks Detection (PPD) Algorithm detects the period first and then looks for all peaks. The reason is the reality of high degree of randomness in the ECG/EKG signals. This randomness makes looking for peaks erroneous process. What we would get is the level of correlativity these signals have.

Our PPD algorithm computes the required parameters: heart period, peaks P, Q, R, S, T, and U, and inter-peak time spans. Peak height and inter-peak time ranging outside normal values, which indicates different kinds of diseases, are detected with our algorithm. The algorithm consists of two execution flows: one that finds the period using the autocorrelation function, and another one that finds the number, amplitude and time interval of the peaks. For the case of process 1 (see Figure 2), we find the discrete derivative of the ECG/EKG signal. The advantage of taking the derivative, and thus adding some overhead to the code, is that the fluctuations taking place in the signal and especially those around the peaks would be reduced to a near-zero-value. In addition, performance overhead associated with derivative calculation of the ECG/EKG signal is negligible compared to the rest of the algorithm. In process 2, a threshold is used to find the peaks.

![Fig. 1: A typical ECG/EKG signal](image1)

![Fig. 2: PPD Algorithm Processing Flow.](image2)

3.1 Method of PPD Algorithm

The ACF, shown in (1), is a statistical method used to measure the degree of association between values in a single series separated by some lags. The fixed length ACF is defined by (2). The main idea is that if we run
the ACF on the function \(y\) over the data sample recorded, and then we can get the coefficients of the ACF.

\[
R_y[k] = \sum_{n=-\infty}^{n=\infty} y[n] \times y[n-k] \quad (1)
\]

\[
R_y[L] = \sum_{n=0}^{N} y[n] \times y[n-L] \quad (2)
\]

where \(R_y\) is the autocorrelation function, \(y[n]\) is the ECG/EKG filtered signal, and \(L\) is a positive natural number related to the number of times needed for the calculations to get the period, same as the number of lags of the autocorrelation.

The main idea for \(L\) comes from the fact that if we minimize the calculations, then our convergence to a solution will be faster. The smaller \(L\) is, the less \(R_{y[n]}\) calculations we would need, since \(N - L\). Now, in case \(y(t)^2\) is periodic with period \(T\), then every \(T\) seconds\(^4\) the multiplication of the signal \(y(t)\) by the signal \(y(t-T)\), would witness two identical signals being multiplied.

\[
T = \frac{n_{\text{period}}}{f_s} \quad (3)
\]

where \(n_{\text{period}}\) is the number of indices needed to have a period, \(f_s\) is the sampling frequency.

If we run the autocorrelation over a signal \(y\), and if the signal is periodic, then every time there is an overlap with the periods\(^5\), we will have a peak in the ACF(\(y\)=\(R_{y[n]}\)).

As we earlier stated, it is important to set a threshold to find the peaks. However, to set thresholds in a method, where we do not take a peak to be a maximum by mistake is dependent that the difference between the maximum peak and the other ACF peaks is significant. One solution is to transform the input signal \(y\) to a signal, whose peaks are exaggerated and whose small values are made nearer to zero.

The derivative function is the beat function we can run that can aid the purpose of increasing the signal peaks and at the same time not consuming a lot of arithmetic operations that may tire the system in time and power. Therefore, after reading the data of the signal \(y\) with samples from the memory, a very helpful step is to calculate the derivative of the signal \(y(t)\). Thus, we the derivative as follows:

\[
\frac{\partial y}{\partial t}(t) \approx y[n+1] - y[n] \\
(n+1) - n = y[n+1] - y[n] \quad (4)
\]

With this derivative, when there is a peak it will be increased with relative to the samples before it, and if the value of \(y[n]\) and \(y[n+1]\) are near to each other (i.e. no peaks) then the difference will look relatively smaller on the new derivative graph.

\(^1\)\(L\) is the number of iterations that we can neglect will be larger

\(^2\)\(t\) is considered with respect to the origin of the analysis-chunk.

\(^3\)\(\text{seconds}\)

\(^4\)corresponding to some \(n\) steps

\(^5\)every \(T\)

### 3.2 Digital Filters

Digital filters process digitized or sampled signals. A digital filter computes a quantized time-domain representation of the convolution of the sampled input time function and a representation of the weighting function of the filter. They are realized by an extended sequence of multiplications and additions carried out at a uniformly spaced sample interval. The digitized input signal is mathematically influenced by the DSP program. These signals are passed through structures that shift the clocked data into summers (adders), delay blocks and multipliers. These structures change the mathematical values in a predetermined way; the resulting data represents the filtered or transformed signal.

Digital filters are a very important part of DSP. Filters have two uses: signal separation and signal restoration. Signal separation is needed when a signal has been contaminated with interference, noise, or other signals. For example, imagine a device for measuring the electrical activity of a baby’s heart (EKG) while still in the womb. The raw signal will likely be corrupted by the breathing and heartbeat of the mother. A filter might be used to separate these signals so that they can be individually analyzed. Signal restoration is used when a signal has been distorted in some way. For example, an audio recording made with poor equipment may be filtered to better represent the sound as it actually occurred.

The general form of the digital filter difference equation is:

\[
y(n) = \sum_{i=0}^{N} a_i x(n-i) - \sum_{i=1}^{N} b_i y(n-i) \quad (5)
\]

where \(y(n)\) is the current filter output, the \(y(n-i)\)’s are previous filter outputs, the \(x(n-i)\)’s are current or previous filter inputs, the \(a_i\)’s are the filter’s feed forward coefficients corresponding to the zeros of the filter, the \(b_i\)’s are the filter’s feedback coefficients corresponding to the poles of the filter, and \(N\) is the filter’s order.

Finite Impulse Response (FIR) filter is basic types of digital filter. FIR filters have no non-zero feedback coefficient in the general form of the digital filter difference equation is (5). That is, the filter has only zeros, and once it has been excited with an impulse, the output is present for only a finite \(N\) number of computational cycles.

The FIR filter use noise rejection and waveform extraction for ECG/EKG algorithm necessary. The data from analog/digital converter is finite and discrete digital signal. Therefore, this ECG/EKG system uses FIR filter. This filter is popular taste in liner digital filter and the most safety in another filter within finite data. The FIR filter is composed of three parts: delay element, multiplier, and adder. Figure 3 shows the basic block diagram for an FIR filter of \(N\) order. And, the following is difference equation that is defined by the relationship between input signal and output signal.

\[
y[n] = a_0 x_n + a_1 x_{n-1} + \ldots + a_N x_{n-N} \quad (6)
\]

\[
= \sum_{i=0}^{N} a_i x_{n-i} \quad (7)
\]
The $N$ is filter order, that correspond to the number of tap\(^6\). The $x_n$'s are current or previous filter inputs. The $y[n]$ is the current filter output. The $a_i$'s are the filter’s coefficients, there corresponds impulse response. An FIR filter works by multiplying an array of the most recent n data samples by an array of constants, and summing the elements of the resulting array. The filter then inputs another sample of data and repeats the process.

$$y[nT] = 2y[(nT - T)] - y[(nT - 2T)] + x(nT) - 2x[(nT - 6T)] + x[(nT - 12T)]$$ \quad (8)

where $T$ is the sampling period, the cutoff frequency is about 11 Hz.

**4.3 FIR Filter**

**4.3.1 Bandpass Filter**

The bandpass filter reduces the influence of muscle noise, 60 Hz interference, baseline wander, and T-wave interference. This filter cascaded the low-pass and high-pass filters described below to achieve a 3 dB passband from about 5-11 Hz.

**4.3.2 Low-pass Filter**

The difference equation of the filter is

$$y(nT) = 32x[(nT - 16T)] - [y[(nT - T)] + x(nT) - x[(nT - 32T)]$$ \quad (9)

where the cutoff frequency is about 5 Hz.

**4.4 Processing**

Correlation is calculated between the acquired segment and a pattern which has been previously obtained. The pattern segment is assumed to contain a regular ECG/EKG signals for the analyzed patient where a signal QRS complex is contained so that any further ECG/EKG pulses can be correlated with it. High correlation values correspond to pulse detection. Pattern extraction is performed by the main processor. Once obtained, it is transferred and stored to the off-chip memory. The off-chip memory starts to receive data samples directly from the ADC. Data samples are stored in a Queue (FIFO). Correlation pattern is calculated, and pulse alignment is evaluated. When the input signals in the Queue is aligned with the pattern, a high correlation value will be obtained, and a signal indicating the presence of a new pulse is generated.

**5 Evaluation Methodology**

Figure 6 shows the block diagram of our system. Signal reading parts consist of ADC, Master CPU and Master On-chip Memory. Filtering parts consist of FIR Filter, Master CPU, Master On-chip Memory, SDRAM and SDRAM Controller. Analysis parts consist of DSP, Slave CPU, Slave On-chip Memory, SDRAM and SDRAM Controller.
Controller. Display parts consist of VGA, VGA Controller, SDRAM, SDRAM Controller, Master CPU and Master On-chip Memory. Table 1 shows preliminary hardware evaluation result of our system. We have to note here that this result is preliminary.

### 6 Conclusion

This paper presents novel algorithm, named Period-Peak Detection (PPD) algorithm, for efficient human heart signals analysis via the use of modern embedded MCSoC architecture. Our solution paves the way for fast and accurate ECG/EKG processing and diagnosis of heart-related diseases. The ECG/EKG algorithm and the system architecture are presented in a fair amount of details. Currently we are working on the complete software and hardware design and testing.

### References


