PULSE BASED SIGNAL PROCESSING FOR SYSTOLIC PEAK RECOGNITION

Gabriel Nallathambi, Jose C. Principe

Department of Electrical and Computer Engineering, Gainesville, Florida, 32611, USA.

Convergent Engineering, Newberry, Florida-32669, USA.

ABSTRACT

Ultra low power wearable wireless patient monitoring systems will be critical for continuous remote monitoring of patients and fast transmission of data to medical personnel for timely intervention. This paper proposes a pulse based methodology for photoplethysmogram (PPG) feature discrimination using the time-based integrate and fire (IF) sampler for continuous, portable pulse oximetry. The analog PPG is transformed into a sequence of time events where the time between two events represents a constant area under the analog PPG signal, with injective mapping between the two domains. A simple and robust method is formulated that directly estimates the systolic peak time from the output of the IF sampler. The proposed processing method can be implemented in hardware using simple combinatorial logic and is comparable to performance of existing digital signal processing methods in the literature.

Index Terms—Integrate and fire sampler, inter-pulse interval, pulse oximetry, pulse rate.

1. INTRODUCTION

Recent advancements in wearable computing have led to the development of continuous wireless patient monitoring body sensors that are potentially non-invasive and unobtrusive. These sensors have the capability to provide timely information about the vital signs of the body [1]. However, to ensure successful practical deployment, these sensors still require the development of signal processing architectures with better resolution, low power consumption, data rates, complexity and better form factor [2], [3].

Signal processors typically use analog to digital converters (ADC) to represent a bandlimited signal using uniform sampling, which relies on a worst case condition, i.e., Nyquist criterion. However, this type of sampling also referred to as redundant sampling, is not efficient in applications where only specific regions are of interest as in biomedical signals and it leads to bulky circuits with large consumption of power. Moreover, boundaries in current technology scaling increasingly limits higher resolutions in the voltage domain.

Ongoing efforts in current and next technologies have resulted in faster digital circuits; therefore, the resolution in the time domain is constantly improving and is more accurate than previous generations [4]. This has led to the development of input dependent, time-based samplers such as Integrate and fire (IF) analog to pulse converters where the analog signal is encoded in a series of time events rather than uniformly spaced amplitude values as is conventionally done in Nyquist samplers [5]. Since the mapping between the amplitude of the analog signal and time events is injective under a finite bandwidth assumption, the IF pulse train representation is as precise as conventional ADC’s with a unique inverse [6]. The IF sampler has been applied in electrocardiogram (ECG) [7] and neural recordings [8]. Moreover, the IF sampler is designed with constraints such as low power, area, bandwidth and resolution; therefore, it is suitable for continuous, ambulatory long-term monitoring using body sensors [5].

In this paper, we study the application of time based sampling for pulse oximetry. Photoplethysmogram (PPG), an optical signal obtained non-invasively using a pulse oximeter, records the pulsatile volumetric changes of blood in the arteriolar bed of tissues [9]. Due to its ease of use, pulse oximetry is ubiquitously employed in hospitals to monitor cardiac health and assess vascular function. Recently, power-efficient, wearable PPG sensors are gaining prominence for continuous, long-term monitoring in home health and telemetry systems [10], [11]. These ultra-low power PPG sensors also bring about the need for lower power, less complex algorithms to identify the different features of the PPG signal. Since the IF pulses consist of localized sparse events in time, the IF sampler is an attractive hardware solution for continuous, low power pulse oximetry as long as we can find algorithms that recognize reliably the waveform features in the pulse domain.

In this paper, we propose to sample the analog PPG signal using an Integrate and fire (IF) analog to pulse converter. The IF sampler encodes the analog PPG signal into a series of time events (pulses) where the time between two events represents a constant area under the analog curve [5]. We also propose schemes for recognizing the systolic peak of the PPG signal. The proposed time-based recognition method identifies the time event corresponding to the systolic peak time by quantifying in real time the time...
structure of the IF pulse train using inter-pulse intervals (IPI), which requires only a few digital counters and comparators that can be implemented in ultra low power VLSI. This approach circumvents the need for additional post processing and enables online identification of features of the PPG signal directly from sampled pulse train.

2. TIME ENCODING OF THE PPG SIGNAL

2.1. Overall architecture

The proposed signal processing architecture for pulse oximetry consists of two main modules: (1) time encoding module and (2) time computation module. In the time encoding module, the PPG analog signal is processed to remove the noise and artifacts. Here we use a digital preprocessor to compare results with alternative solutions published in the literature, but the preprocessing can be also implemented in analog hardware. Then the IF sampler converts the PPG signal into a series of time pulses to generate the IF pulse train. The sequence of pulses is then fed to the time computation module where signal processing is done in the pulse domain to recognize the different features of the PPG signal directly from the time between the pulses. Fig. 1 shows the process flow of the proposed method and the steps involved are explained subsequently.

Fig. 1. Process flow of the time encoding scheme.

2.2. Preprocessing

The PPG signal has a slowly varying baseline due to respiration and other low frequency components which creates difficulties in the analysis [9]. To remove the low frequency trends, an adaptive zero frequency notch filter [12] is employed.

The adaptive filter uses LMS algorithm with a single weight as described in [13]. The target signal is the PPG signal corrupted by baseline wander and the input to the filter is a constant. The step size of the filter was chosen to give a cut-off frequency of 0.3 Hz, which is within the limit of 0.8 Hz specified for high pass filtering of biomedical signals [14]. Research has shown that these adaptive filters can be fabricated in continuous time, low-power analog VLSI [15]. A low pass filter with cut-off frequency of 40 Hz was also used to remove powerline noise and other high frequency components as shown in Fig. 2.

2.3. Integrate and fire sampler

The goal of the IF sampler is to represent the continuous amplitude signal in a compressed manner with its output codifying the variation of the integral of the signal [5], [6] and create an injective mapping (one to one with a unique inverse) between the two representations. IF sampler is inspired by the working of a simplified biological neuron model from computational neuroscience. One of the main advantages of the IF sampler is the simplicity and power-efficiency of the hardware circuitry which makes it a perfect candidate for long-term ambulatory, ultra-low power monitoring. The area and power consumption of IF sampler is smaller than most of the ADCs available: a single channel IF has ~ 30 transistors, with a layout box of 100 μm X 100 μm using CMOS 0.6 μm technology and with a figure of merit (FOM) of 0.6 pJ/conv for an 8 bit converter [5]. By taking advantage of the signal time structure, the IF sampler reduces the sampling rate by a factor of 4, at least for the impulsive class of signals, with respect to Nyquist samples.

In Fig. 3, we show the block level schematic of the IF sampler.

Fig. 3. Schematic of IF sampler.

Let $x(t)$ be the analog continuous time signal and $g(t)$ be the “averaging function” given by $g(t) = e^{\alpha(t-t_0)}$, where $\alpha$ is the leak value and $t_0$ is the starting time of the continuous signal $x(t)$. The analog signal $x(t)$ is convolved with $g(t)$ and the result is compared against two fixed thresholds. If the integrated value reaches or exceeds the positive threshold ($\theta_p$), a positive pulse is generated at that time instant; similarly, if the integrated value reaches or
exceeds the negative threshold \( (\theta_n) \), a negative pulse is generated at that time instant. Then, the sampler is held at this state for a specific duration given by the refractory period \( \tau \). This prevents spurious pulse representations and then the integrator is reset. Thus, 
\[
\theta_k = \int_{t_k}^{t_{k+1}} x(t)e^{\alpha(t-t_k)}dt
\]
where \( \theta_k \) can be \( \theta_p \) or \( \theta_n \) and \( \alpha, \tau > 0 \).

The series of time events (pulses) of positive or negative polarity obtained by this process is referred to as a pulse train. The injective mapping between the analog and pulse domains with a unique inverse between the two representations allows the reconstruction of the signal from the IF pulse train [6]. The choice of IF parameters governs the average pulse rate (APR) and signal to noise ratio (SNR) as shown in Fig. 4. In Fig. 4b, the following IF parameters were chosen: \( \theta_p = -\theta_n = 0.001, \alpha = 40, \tau = 1 \text{ ms} \). This results in an APR and SNR of 289 pulses/sec and 36 dB respectively. In another example, the IF parameters were chosen as \( \theta_p = -\theta_n = 0.001, \alpha = 40, \tau = 100 \text{ ms} \) in Fig. 4c and the APR and SNR were approximately 9 pulses/sec and 18 dB respectively. Thus by varying the IF parameters, the APR and SNR can be changed drastically.

The trade-off associated with IF parameters and their effect on SNR and APR has been discussed elaborately in [16]. In the rest of the paper, the IF sampling parameters \((\theta_p = -\theta_n = 0.001, \alpha = 40, \tau = 10 \text{ ms with APR = 70 pulses/sec}, \text{SNR} = 34 \text{ dB})\) as a compromise between number of pulses and time resolution [7].

3. TIME BASED RECOGNITION OF SYSTOLIC PEAK.

Among the features of the PPG signal, the time of systolic peak occurrence is most widely used for calculating heart rate, pulse transit time and pulse rate variability [9]. In fact, accurate automatic recognition of the systolic peak is the first step in pulse-wave analysis of the PPG and often the other features of PPG such as tidal and dicrotic waves are delineated with respect to the systolic peak [17]. Therefore, it is necessary to recognize the systolic peaks reliably and accurately with low computational power.

Methods based on rules [17], derivatives [18], slope sum function [19] and moving averages [20] have been proposed in the literature for finding the systolic peak of the PPG. For instance, Jang et al. detects systolic peaks as the maximum between pulse onsets found with knowledge-based rules that are derived from morphological information [17]. Li et al. utilized the first derivative of the signal to delineate the inflection and zero crossing points wherein the systolic peak corresponds to the first zero crossing point after the inflection point [18]. Zong et al. employed a windowed and weighted slope sum function to enhance the upslope of the signal and then adaptive thresholds combined with search strategy was used to identify systolic peak [19]. Elgendi et al. used two event-related moving averages to generate blocks-of-interest corresponding to systolic peak areas and beat areas respectively, and the systolic peak is identified by comparing the width of the block against a threshold [20]. However, these methods cannot be directly applied to the output of time-based samplers. The alternative is to perfectly recover the analog signal, which is a power consuming step, and then apply these methods. In this paper, we propose to work directly on the pulses without reconstruction and use simple logic to identify the systolic peak.

Fig. 4. Generation of IF pulse train. (a) Preprocessed analog PPG signal. (b) Example of IF representation. (c) Example of extremely sparse IF representation.

3.1. PPG signal processing in the pulse domain

The information in the pulse domain is contained in the timing between pulses and their corresponding polarity; therefore, the extraction of information has to be done on
the time structure of the bipolar pulse trains [7]. In our previous work [7], we had shown that the fiducial points of ECG can be recognized from a set of five attributes/features, derived from the pulse train, by imposing decision rules on the attribute vector. In this paper, we show that the IPI by itself is sufficient to discriminate the systolic peak i.e., it can be obtained directly from the pulses without any additional post-processing.

To process the IF pulse train, we define a syntactic approach where each pulse generated by the IF sampler is considered an IF alphabet. The timing and polarity that make up each pulse constitutes the IF letters. Then we define the notion of IF word which is an aggregation of IF alphabets (pulses) of the same polarity. The IF words can be positive or negative depending on the polarity of the underlying pulses. The systolic peak of PPG occurs in the positive IF word. Thus all IF alphabets of positive IF words are candidates for systolic peak.

3.2. Pulse domain systolic peak recognition without thresholding

To recognize the IF alphabet corresponding to systolic peak, we use IPI between the pulses, which represent the instantaneous slope at each time instant. So, the systolic peak time is given by the time of the minimum IPI within the positive IF word.

The process is graphically illustrated in Fig. 5. Sporadically, there are spurious IF words due to motion artifacts which results in false detections. This can be avoided by using a thresholding scheme as described in Section 3.3.

3.3. Pulse domain systolic peak recognition with thresholding

To reduce the false detections without bringing more sophisticated rules, we employ a thresholding technique where the minimum IPI in each positive IF word is compared against a fixed threshold. Then, the systolic peak time corresponds time of the interval that does not exceed the threshold i.e., its amplitude is high enough to correspond to a systolic peak.

The threshold is calculated from the first five seconds of the pulse train and is empirically given by (thresh_level*\(m_l\)) where \(m_l\) is the mean of the lower half extremities of the minimum IPI in the positive IF words and thresh_level is a constant.

4. PERFORMANCE EVALUATION

4.1. Materials

We assessed the performance of the proposed algorithm using PPG signals acquired under IRB approval from prenatal care at Shands Medical Plaza, Florida. Presently, there are no benchmark databases to evaluate the performance of fiducial point recognition of PPG signals. Therefore, to assess the quality, we simultaneously recorded ECG signals using chest leads. The signals were acquired by a data acquisition system designed by Convergent Engineering, Inc, Newberry, FL. The PPG signals recorded from Shands Medical Plaza were sampled at 100 Hz and the ECG signals were sampled at 500 Hz. We used one minute recordings from 180 patients for analysis.

4.2. Quantitative measures

Benchmark metrics such as sensitivity, positive predictive value and detection error rate are employed to quantitatively evaluate the performance of the detector. They are defined as follows: $S_e = \frac{TP}{TP+FN}$, $P = \frac{TP}{TP+FP}$, $Error = \frac{FP+FN}{TP+FN}$ where TP is the number of true positives which refers to systolic peaks that are correctly detected, FN is the number of false negatives which refers to systolic peaks that are not detected, FP is the number of false positives which refers to falsely detected systolic peaks. The R peaks of ECG were used as a corrective reference to determine TP, FP and FN, while allowing a tolerance of 0.2s to allow for the physiological delay due to pulse transit time.

In addition to the benchmark metrics, we also used the following metrics based on credible intervals (CI) to determine the number of reliable peaks that can be used for further computation of other vital parameters such as pulse rate variability and pulse transit time:

1. Percentage of credible intervals (pCI): We have defined CI as a one-to-one correspondence between the R peak of ECG and systolic peak of PPG, i.e., only one systolic peak between two consecutive R to R intervals. pCI is simply the ratio of the number of credible intervals to the total number of intervals.
2. Mean square error (MSE) of CI: Ideally, the RR intervals and the corresponding systolic peak intervals must agree with each other. So, we computed the MSE between consecutive RR intervals and their corresponding systolic peak intervals. Since the outliers are useless for this purpose, we will only consider the intervals that are credible. The MSE of CI is defined as

$$MSE = \frac{1}{N} \sum_{n=1}^{N} (RR_n - SS_n)^2$$

where $RR_n$ is the nth RR interval, while $SS_n$ is its corresponding nth interval between consecutive systolic peaks and $N$ is the total number of credible intervals.

5. RESULTS AND DISCUSSION

The performance of systolic peak recognition was assessed using the IF sampler parameter values described in Section 2. Fig. 6 shows an evaluation of systolic peak recognition with the proposed method.

To evaluate the performance of systolic peak recognition, the R-peak of ECG was also detected simultaneously. A total of 15061 R peaks were detected from the ECG of 180 patients using the Pan-Tompkins algorithm [21]. The location of R-peaks were used for labelling the systolic peaks and were not used for any other purposes in the algorithm.

![Fig. 6. (a) Detection of systolic peak times of PPG with the proposed method. (b) Detection of R peak times of ECG using Pan-Tompkins algorithm. The dotted vertical lines indicate the time of occurrence of the peaks.](image)

Fig. 7 shows the variation of the benchmark metrics as a function of threshold level. It is clear from the figure that initially the performance of the algorithm with thresholding offers a balance between the different performance metrics i.e., thresh_level is between 6 and 15. However, within a few threshold levels the performance of the algorithm with thresholding approaches the performance of the algorithm without thresholding. For the rest of the paper, the value of thresh_level was chosen as 6. Table I reports the algorithm’s performance using the proposed metrics. As described in Section 2, increasing the pulse rate results in better systolic time resolution and vice-versa. However, systolic peaks can be detected as long as the positive IF words are represented in the pulse train.

![Fig. 7. Effect of variations in the level of threshold on the performance of the proposed method.](image)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Li et al.’s method [18]</th>
<th>Proposed method Without thresholding</th>
<th>Proposed method With thresholding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systolic peaks detected</td>
<td>14812</td>
<td>15463</td>
<td>14997</td>
</tr>
<tr>
<td>TP</td>
<td>14693</td>
<td>14867</td>
<td>14777</td>
</tr>
<tr>
<td>FP</td>
<td>33</td>
<td>479</td>
<td>118</td>
</tr>
<tr>
<td>FN</td>
<td>263</td>
<td>79</td>
<td>154</td>
</tr>
<tr>
<td>CI</td>
<td>14667</td>
<td>14400</td>
<td>14653</td>
</tr>
</tbody>
</table>

The results with the proposed method are comparable to the existing methods in the literature such as Li et al. which in turn is comparable to the other methods discussed in Section 3 [18]. Li et al. [18] utilizes derivatives and inflection points along with amplitude and interval criteria, while here we only use the minimum IPI to find the peaks. From the results, it can be seen that the number of false detections in the proposed method are significantly reduced with thresholding, and it creates far fewer false negatives than [18]. This is important in ambulatory monitoring and the proposed method with thresholding offers a balance between the number of false negatives and false positives, whereas other methods have a disproportionate number of false positives or negatives. Also, the accuracy of detection can be improved further by providing automatic gain control in the pulse domain, which will be discussed in a future publication.
Thus, the proposed method reliably determines the systolic peak directly from the sampled data using a simple detection scheme. The big appeal of pulse based signal processing is that feature extraction and quantification can be implemented in combinatory logic alone, using exclusively time features; therefore, processing becomes non-numeric and uses a fraction of the digital signal processor power. The IF sampling and computational method can be implemented in hardware and is suitable for real time implementation with ultra-low power electronics for ambulatory monitoring.

6. CONCLUSION

In this paper, we studied using time-based IF sampler for continuous portable pulse oximetry. The IF representation maps the analog PPG signal into a series of time events, with fidelity similar to conventional ADC, but allows for a nonnumeric signal processing methodology that can be implemented with combinatory logic. The precise time structure of the pulses allows the formulation of simple processing schemes to identify the points of interest that do not require numeric computations. We have proposed and evaluated a new way of recognizing systolic peaks in the PPG signal. Our ultimate aim is to show that the entire contour analysis of PPG signal can be done in the pulse domain after using an IF sampler. This enables an ultra-low power hardware only solution for continuous monitoring and diagnosis in wireless body area networks and other personalized medicine applications.

REFERENCES