Adaptive Pulse Width Control and Sampling for Low Power Pulse Oximetry

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Abstract—Remote sensing of physiological parameters could be a cost effective approach to improving health care, and low-power sensors are essential for remote sensing because these sensors are often energy constrained. This paper presents a power optimized photoplethysmographic sensor interface to sense arterial oxygen saturation, a technique to dynamically trade off SNR for power during sensor operation, and a simple algorithm to choose when to acquire samples in photoplethysmography. A prototype of the proposed pulse oximeter built using commercial-off-the-shelf (COTS) components is tested on 10 adults. The dynamic adaptation techniques described reduce power consumption considerably compared to our reference implementation, and our approach is competitive to state-of-the-art implementations. The techniques presented in this paper may be applied to low-power sensor interface designs where acquiring samples is expensive in terms of power as epitomized by pulse oximetry.

Index Terms—Design-space analysis, low-power, pulse oximetry, SpO2, tracking-loop.

I. INTRODUCTION

INFANT mortality in rural India is substantially higher than in the developed world [1]. The Remote Neonatal Intensive Care Unit (RNICU) Project aims to provide affordable health care in rural areas by monitoring various physiological parameters of neonates, remotely [2]. To remotely monitor physiological parameters, it is desirable to have sensor nodes that are small and discreet, and the battery powering those nodes would therefore be of limited capacity. To reduce the frequency of battery replacement, a sensor node that consumes as little power as possible has to be designed.

Arterial oxygen saturation is an important physiological parameter in modern medicine [3]. Pulse oximeters are commonly used in intensive care units, sleep studies, neonatal care etc. [3]–[6]. Low-power pulse oximeters are useful for remotely monitoring heart rate and oxygen saturation [7]–[14].

In this paper, we present a novel low-power pulse oximeter. First, we propose a photocurrent detector architecture that uses a time-to-digital converter (TDC) and perform design-space analysis to optimize the circuit parameters. Second, we describe a technique to estimate SNR of the captured photoplethysmogram and use this information to dynamically adjust the LED on-time. This reduces power consumption by operating the sensor at just sufficient SNR. Third, we propose a simple algorithm that reduces the number of samples required, thereby reducing power consumption. Finally, we evaluate power benefit of the proposed dynamic adaptation techniques.

There have been numerous efforts in the past to reduce power consumption in pulse oximetry. A photodiode structure that lowers power consumption in the photodiode interface circuit is proposed in [15] and a method to optimally size the photodiode is described in [16]. Our work, however, is about designing a low-power interface circuit for a given photodiode. The authors in [17], [18] argue that low power analog circuits are suitable for sensing physiological parameters. A recently proposed photodiode interface circuit targeted to pulse oximetry uses energy efficient transimpedance amplifiers and is a completely analog design [19]. In contrast, the photodiode interface we propose is more digital in nature and employs a time-to-digital converter (TDC). A switched integrator has been used in [20] to reduce noise. Our work complements this design to further reduce power consumption. Although our implementation is similar, it differs in subtle ways. The idea of dynamically reducing power consumption based on the characteristics of the acquired plethysmogram has been claimed in [21]. We propose a way of accomplishing this and measure the power conserved. In [22], compressive sensing is used to minimize power consumption by reducing the number of samples acquired. However, existing photodiode interface circuits use analog band pass filters that do not easily permit sub-Nyquist sparse random sampling, which is necessary for compressive sensing to effectively reduce power. Our work addresses this issue, and the proposed architecture can acquire samples at arbitrary time instants. A trade-off between noise performance required of the photodetector circuit and the duration for which the LED is turned on for each measurement is shown in [23], [24]. We extend this by proposing a power model for opamps in terms of their noise performance. Using this, we optimize the trade-off between burning power in the LED versus the front-end amplifier.

The rest of this paper is organized as follows. First, we briefly review the principle behind pulse oximetry. We then present the proposed photodetector architecture. Next, we describe how it is optimized for power. Section 4 presents a technique that dynamically lowers the duration for which the LED is turned on, and proposes a simple algorithm that further decreases power.
by reducing the number of samples that are acquired. We then evaluate the performance of the proposed pulse oximeter in Section 5. Finally, Section 6 concludes the paper.

II. BACKGROUND

Oxygen saturation is the percentage of haemoglobin in the blood that is oxygenated. If \( [\text{Hb}] \) is the concentration of de-oxygenated haemoglobin in the blood and \( [\text{HbO}_2] \) is the concentration of oxygenated haemoglobin, then

\[
S_{\text{pO}_2} = \frac{[\text{HbO}_2]}{[\text{Hb}] + [\text{HbO}_2]}.
\]

Pulse oximetry is an optical technique to measure arterial oxygen saturation which takes advantage of volumetric pulsations in the arteries as the heart pumps blood. Light from an LED is transmitted through a body part, usually a finger or an ear lobe, and the intensity of the light that passes through to the other side is measured using a photodiode. From [3], the normalized absorption ratio \( R \) is calculated as

\[
R = \frac{P_R}{P_{IR}}
\]

where the perfusion \( P \) is the ratio of AC to DC of the corresponding plethysmogram for red and infra-red wavelengths

\[
P = \frac{I_{pd(ac)}}{I_{pd(dc)}}.
\]

Here, \( I_{pd} \) is the received photocurrent. Substituting absorption coefficient values from [3] gives

\[
S_{\text{pO}_2} = \frac{0.81 - 0.18R}{0.63 + 0.11R} \times 100\%.
\]

In practice however, \( S_{\text{pO}_2} \) is assumed to be a linear function of \( R \) as in

\[
S_{\text{pO}_2} = a - bR
\]

where \( a \) and \( b \) are constants obtained by calibration.

III. PHOTODIODE INTERFACE CIRCUIT

A. Proposed Architecture

The receiver circuit we propose is shown in Fig. 1. To acquire a sample, the analog circuitry and the TDC are powered up, one of the LEDs is turned ON, and the switch S1 is opened. The first stage is a current integrator which converts the photocurrent to a voltage ramp. The amplified ramp is then thresholded against two voltage references. Finally, a time-to-digital converter (TDC) measures the difference between the times when the amplified ramp hits the two reference voltages. After the measurement is recorded, the LED, the entire analog circuitry, and the TDC are powered down to save power. Fig. 2 shows this process and Fig. 3 illustrates the output we expect from the TDC for one of the channels (red or IR). It is a discrete time waveform with samples separated by 10 ms. To acquire each sample, the switched integrator in Fig. 1 accumulates photocurrent for a duration that typically lasts a few hundred microseconds, and the measurement made by the TDC is recorded. As illustrated in Fig. 3, the recorded plethysmogram has a large DC component and a small AC component.

Suppose that the circuit starts to acquire a sample at \( t = t_1 \). The output of the first stage is

\[
V_1(t) = \frac{I_{pd}t}{C}
\]

where \( I_{pd} \) is the photocurrent. This is amplified by the second stage to give

\[
V_2(t) = A \frac{I_{pd}t}{C}
\]
where $A$ is the gain of the second stage. After thresholding, the TDC measures

$$t_{tdc} = t_{r2} - t_{r1} = \frac{C}{A_{pd}} \delta V_r$$

(8)

where $\delta V_r = V_{r2} - V_{r1}$. $t_{r1}$ and $t_{r2}$ are the instants when $V_2(t)$ crosses $V_{r1}$ and $V_{r2}$ respectively. Thus, $t_{tdc}$ is inversely proportional to the photocurrent [25]. It can be shown that (Appendix A) the perfusion is

$$P = \frac{t_{tdc(ac)}}{\tau_{dc(fd)}}$$

(9)

Even if the photocurrent $I_{pd}$ is a constant, the output of the TDC will exhibit variance due to noise. This is illustrated in Fig. 4. To quantify the effect of noise, we define signal-to-noise ratio (SNR) of the acquired plethysmogram as follows [23].

$$\text{SNR} = \frac{t_{tdc(ac)}}{\sigma_{tdc}}$$

(10)

where $\sigma_{tdc}$ is the standard deviation of the jitter in the output of the TDC due to noise. It can be shown (Appendix B) that

$$\text{SNR}^2 = \frac{I_{pd(ac)}^2}{A^2 \left( \frac{2v_{ln}^2\omega_{n1}}{A_{n1} A_{n2} I_{pd(nc)}^2} + A \left( \frac{\omega_{n1}}{C V_{nc}} \right)^2 \right) + A \left( \frac{\omega_{n1}}{C V_{nc}} \right)^2}$$

(11)

where $A_N = 1 + (C_4)/(C)$ is the noise gain of the first stage, $v_{ln}^2$ is the input referred noise spectral density of the opamp used for the switched integrator, $\omega_{nb} = (\omega_{n1})/(A_N)$ is its noise bandwidth and $\omega_{n1}$ its unity gain bandwidth, and $I_{pd, n}$ is the photocurrent noise spectral density.

We employ a switched integrator front-end because it gives a simple way to control the duration of photocurrent measurement. The gain of the second stage can be digitally controlled (but the two reference voltages are held fixed). This allows a control algorithm to analyze the acquired photoplethysmogram and adjust the gain, $A$, to dynamically trade-off SNR for measurement duration [(11) and (8)]. This reduces the power consumption since measurement duration determines the percentage of time for which the LED and the circuitry are powered.

In the proposed circuit, the amplified ramp is thresholded against two references, and the difference between the times when the ramp crosses these two references is measured. This suppresses the effect of $1/f$ noise in the integrator stage, which can be severe because of the very low signal frequency involved (0.5–6 Hz). This is similar to correlated double sampling [26]. However, only the $1/f$ noise from the amplifiers (and not due to the comparator) is suppressed. Comparator $1/f$ noise has a smaller effect on SNR because the signal would have undergone substantial amplification before reaching the comparator. Furthermore, since the power supply to the entire analog circuit is duty cycled, $1/f$ noise gets further suppressed [27]. Moreover, TDC measurements at the peak and trough are subtracted to obtain $t_{tdc(uo)}$, which suppresses comparator $1/f$ noise below the heart rate.

Another aspect of the proposed circuit is that the LED current is fixed so as to enable the LEDs to always operate at their highest efficiency (luminosity per unit current). This is in contrast to implementations such as [19], [28], and [20], that control the current so that the DC value of the red and IR photoplethysmogram are equal to some pre-determined value. By operating each LED at its maximum efficiency point and controlling only the duty cycle, we not only save power but also eliminate one more amplifier that would have otherwise been used to control the LED current. Finally, the proposed circuit uses a time-to-digital converter (TDC) as opposed to an ADC. This is because it is relatively easier to obtain large dynamic range in TDCs in contrast to ADCs, particularly as the supply voltage shrinks.

To deal with low perfusion, current oximeter implementations use AC coupled amplifiers to separate the large DC level from the AC signal. Only the amplified AC signal is fed to the ADC to make the best use of its dynamic range [20], [28]. However, the use of AC coupled amplifiers and low pass filters in the pipeline, as illustrated in Fig. 5, make the process of turning ON the LED and sparsely sampling the photocurrent at arbitrary time instants harder to implement. This is because (a) low pass filters do not allow the plethysmogram to change rapidly as would happen if the LED is turned ON at arbitrary time instants, and (b) it is difficult to build a sample-and-hold circuit.
that droops voltage by no more than a few hundred microvolts over the duration when samples are not taken (on the order of one second). Such a sample-and-hold circuit will need a large capacitor as well as additional circuitry to isolate it from other amplifiers whose power supply is being duty cycled. These are undesirable in both integrated and discrete implementations.

TDCs solve this problem by offering very large dynamic range, thereby permitting the photocurrent to be digitized directly without having to separate the AC signal from the DC. For example, a 22-bit TDC with a resolution of 110 ps was demonstrated in [29]. With such a large dynamic range, even under low perfusion, quantization noise is sufficiently small. Furthermore, because the samples are separated by a relatively large interval of 5 ms, some TDC architectures such as Vernier TDCs may comfortably take more time than the sampling duration to resolve the time difference.

On the flip side, the noise bandwidth in Fig. 1 is the full circuit bandwidth, whereas the noise bandwidth in Fig. 5 is limited to the signal bandwidth,\(^1\) which is usually about 6 Hz. The excess noise bandwidth is the price for the ability to sample at arbitrary time instants and to power down the entire circuit between samples.

Having decided on the architecture, we proceed to select the parameters of the amplifiers in Fig. 1. In selecting the gain, bandwidth, and noise performance of the amplifier, a trade-off presents itself. The higher the gain-bandwidth and lower the input referred noise level of the amplifier, the larger will be its bias current and lower will be the necessary measurement duration to achieve a target SNR leading to smaller power burnt in the LED (because it can be shut off sooner). Conversely, using an amplifier with smaller gain-bandwidth and poorer noise performance will lead to lower power burnt in the amplifier. However, the duration of measurement will now have to be longer to achieve the desired SNR, which means that more power is burnt in powering the LED while the photocurrent is being measured. To optimally select the parameters of the amplifier, we develop a power model for opamps in terms of bandwidth and noise performance. We then perform design-space analysis.

### B. Interface Circuit Design

The photocurrent \(I_{pd(dcc)}\), perfusion \(P\), photodiode capacitance \(C_{pd}\), and photocurrent noise spectral density \(i_{pd,n}\) are known. We design the circuit parameters \(C\), \(V_{r1}\), and \(V_{r2}\), and also the gain, bandwidth, and input referred noise levels of the opamps in Fig. 1. These parameters are chosen so that the total power consumption of the LED and the interface circuit is minimized. For the following analysis, only the noise from the first stage is considered, and the second stage is assumed to have unity gain. We also assume that \(V_{r1}\) and \(V_{r2}\) are fixed and explain later how we choose \(V_{r1}\) and \(V_{r2}\).

1) Gain: If the desired average duration for turning on the LED to acquire a sample is \(t_{on(avg)}\), the integration capacitor, \(C\), is set to be

\[
C = \frac{I_{pd(dcc)}t_{on(avg)}}{V_{r2}}.
\]  

(12)

This sets the noise \(A_N\) at \((1 + (C_{pd}/C))\). At this point, the value of \(t_{on(avg)}\) at which the total power consumption will be minimized is not known. This will be the subject of a subsequent section.

2) Bandwidth: The output of the switched integrator, \(V_{i}(t)\) in Fig. 1, will not be a perfect ramp because the bandwidth of the opamp is limited (see Fig. 6). We choose the minimum bandwidth that keeps non-linearity below the acceptable level. In order to do this, it can be shown that the opamp bandwidth has to satisfy

\[
\frac{\omega_{ihb}}{t_{i}} - \frac{\omega_{ihb}}{t_{i}} \geq \text{SNR}_{r}
\]  

(13)

where \(\text{SNR}_{r}\) is the minimum SNR necessary to make sufficiently accurate \(\text{SpO}_2\) calculations [23]. \(\omega_{ihb} = (\omega_{ag})/(A_N)\) is the noise bandwidth, and \(\omega_{ag}\) is the unity gain bandwidth. This equation has to be solved iteratively to find the minimum acceptable bandwidth for a given \(t_{on(avg)}\). Equation (13) indicates that as \(t_{on(avg)}\) is increased, the required bandwidth reduces.

3) Input Referred Noise: Referring the jitter in the output of the TDC \((\sigma_{tdc})\) back to the input of the opamp [30], the maximum permissible input referred noise spectral density of the opamp (above which the SNR of the acquired plethysmogram will become lower than \(\text{SNR}_{r}\)) can be shown to be

\[
t_{in,n} = \frac{\delta V_{r2}I_{pd(dcc)}t_{on(avg)}}{2V_{r2}A_{v}C\omega_{nh} \text{SNR}_{r}V_{r2} - \frac{i_{pd,n}^2}{I_{pd(dcc)}^2}}
\]  

(14)

Equation (14) (derived in Appendix B) shows that as \(t_{on(avg)}\) is increased, the input referred noise requirement gets relaxed.

4) Reference Voltages: It is desirable to choose \(V_{r1}\) and \(V_{r2}\) that are as high as possible within the input common mode range

\[1\]High frequency noise in the circuit before the sample-and-hold (S/H) stage aliases into the signal band. This results in higher noise than if the LED was kept continuously ON without the S/H stage.

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Fig. 5. Photocurrent detector based on transimpedance amplifier.

Fig. 6. Illustration of the non-ideal switched integrator output.
of the comparator so that the noise performance of the comparator is optimized. If \( V_{r1} \) and \( V_{r2} \) are close to each other, \( \delta V_r \) becomes small, and from (14), the permissible input referred noise of the opamp reduces, which in turn causes an increase in the opamp power consumption. On the other hand, if they are far apart, from (13), the bandwidth required increases, which also causes an increase in the power consumption of the opamp. This may be intuitively understood from Fig. 6 which illustrates the output of the switched integrator. If \( \delta V_r \) is small, the output is closer to a straight line between \( V_{r1} \) and \( V_{r2} \). On the other hand, if \( \delta V_r \) is large, a larger portion of non-linearity gets captured. As a compromise, we choose \( V_{r1} = 1.25 \) V and \( V_{r2} = 2.5 \) V. Small variations in the reference voltages due to comparator offset or reference generator offset are insignificant because we use only the ratio of readings and the voltage reference terms get canceled.

### C. Op-Amp Power Model

We would like to estimate the power consumption of an opamp, given its gain, bandwidth, and input referred noise level. To do this, we assume that the opamp is constructed by cascading a number of simple amplifiers, each having a gain of 10. Consequently, the required number of stages is

\[
\log_{10}(A_{V_{\text{total}}}) = \log_{10}(A_{V_{\text{total}}}) \times I_{D_{ps}}
\]

where \( I_{D_{ps}} \) is the current per stage. The bandwidth is approximated [31] by

\[
BW = K_1 I_{D_{ps}}
\]

where \( K_1 \) is a model parameter.

We ignore 1/f noise in this model because the proposed circuit is designed to be resistant to 1/f noise and approximate input referred noise [31] as

\[
\mathcal{v}_{in,n}^2 = K_2 \frac{BW}{I_{D_{ps}}},
\]

where \( K_2 \) is a model parameter. Given the input referred noise and the bandwidth, we choose \( I_{D_{ps}} \) as

\[
I_{D_{ps}} = \max\left(\frac{BW}{K_1}, \frac{K_2 \cdot BW}{\mathcal{v}_{in,n}^2}\right).
\]

Therefore, the current consumption of the opamp according to our model is

\[
I_{D_{\text{total}}} = \log_{10}(A_{V_{\text{total}}}) \times \max\left(\frac{BW}{K_1}, \frac{K_2 \cdot BW}{\mathcal{v}_{in,n}^2}\right).
\]

Fig. 7. Scatterplot of supply current versus bandwidth on a log-log scale for discrete opamps. \( K_1 = 1.32 \cdot 10^{21} \).

Parameters \( K_1 \) and \( K_2 \) were obtained from least mean squares fits performed in MATLAB using data from 35 discrete opamps from Texas Instruments with input bias currents below 50 pA [32]. Figs. 7 and 8 show scatterplots of supply current against opamp parameters and the least mean squares fit. The mean of the absolute relative errors is 57.3%. Although this is high, we deem this to be sufficient for reasons that will become apparent when we discuss dynamic adaptation techniques in the next section.

### D. Trade-Off Between LED Power and Amplifier Power

We assume that an SNR of 100 is necessary, perfusion is 1.5%, photodiode junction capacitance is 1 nF, and that the DC value of the photocurrent is 100 nA. With this, we sweep the LED on-time \( t_{\text{on(avg)}} \), compute opamp parameters needed for each \( t_{\text{on(avg)}} \), determine power for that opamp from the previously described power model and then plot the power consumption against LED on-time in Fig. 9.

When designing low-power pulse oximeters, it is tempting to reduce LED on-time aggressively since the LEDs consume a major chunk of power. However, Fig. 9 shows that it is wiser to...
err on the side of higher LED on-time since the slope is much lower when the LED power dominates. The optimal on-time for the probe we used corresponds to 237 $\mu$s, which requires a gain of 106, closed-loop bandwidth of 1 MHz, and an input referred noise of $2nV/\sqrt{Hz}$. In our COTS implementation, the TDC has a resolution of 62.5 ns, and ensuring that the SNR with TDC quantization noise\(^2\) considered is above 100 resulted in the on-time being 416 $\mu$s. This requires a gain of 61, closed-loop bandwidth of 0.6 MHz, and an input referred noise of $4.47nV/\sqrt{Hz}$. Furthermore, the model used does not account for noise from resistors, voltage references, photocurrent noise due to ambient light etc. Because the trade-off curve is much less sharper at higher on-times, it is safer to choose an on-time that is higher than optimal. Thus, the first stage is chosen to have noise gain of 11 with unity gain bandwidth of 3 MHz, and the second stage to have a gain adjustable in the range 1 to 10 with a unity gain bandwidth of 3 MHz.

IV. DYNAMICALLY REDUCING POWER

We present two dynamic adaptation techniques that reduce power by adapting the system to the user of the pulse oximeter.

A. Minimum SNR Tracking

In the previous section, while optimizing the amplifier parameters, we assumed that the perfusion is 1.5% and that the average photocurrent is 100 nA. The average photocurrent depends on the thickness of the finger, tissue perfusion etc., and can vary over an order of magnitude. Perfusion also exhibits considerable variance (0.1% to 5%) and is dependent on the ambient temperature. Furthermore, the noise input into the system depends on ambient lighting and the extent to which ambient light reaches the photodiode. Consequently, the pulse oximeter has to cope with widely varying SNR levels. Because of this, the optimal amplifier parameters determined in the previous section should be treated as a guiding value rather than precise targets to achieve, and this is also why we accepted a rather large relative error in estimating power consumption of amplifiers.

Fig. 10 shows how the SNR varies with measurement duration for three fingers of a volunteer. Existing oximeters deal with large variation in the input SNR by designing the interface circuit with a large SNR margin. This however, causes the system to consume larger power than necessary in majority of the cases. For instance, in Fig. 10, to achieve SNR of 100, the duration for which the LED needs to be turned on (and hence power) is 2.5 times higher for the middle finger than for the forefinger. We propose measuring the SNR of the acquired photoplethysmogram continuously and dynamically adjusting LED on-time (and hence power consumption) so that the system operates at just sufficient SNR. We christen this technique “Minimum SNR tracking”.

The signal level can be estimated by measuring the AC value of the plethysmogram. Since the plethysmogram is known to have mostly low frequency components (most of its energy is in the frequency range of 0.5 to 10 Hz), we filter it to remove all low-frequency content ($<10$ Hz). Assuming that the input noise is white, the filtered waveform should contain only pink noise. The variance of this is calculated and scaled to obtain the noise variance of the acquired photoplethysmogram [33]. Thus SNR is computed.

To evaluate this approach, 400 samples were recorded at high SNR (this was ensured by keeping measurement duration above 1 ms). This high SNR recording was deemed to have infinite SNR. Additive White Gaussian Noise (AWGN) was then added to this recording, and an estimate of the AWGN by the above described method was obtained. Table I shows the performance of blind estimation of noise with a fourth order Butterworth high pass filter. The mean of the estimated noise over 1000 realizations of pseudo-random noise is reported. The proposed blind estimation method works well at low to medium SNR and underestimates high SNRs. It is able to compute SNR readings below 100 satisfactorily with a fourth order Butterworth high-pass filter.

\(^2\)The maximum photocurrent beyond which the TDC quantization noise alone causes the SNR to be lower than acceptable is $I_{\text{PD,dc}} = \sqrt{(C \cdot P \cdot t_{\text{on}})/((A \cdot SNR_{\text{min}} \cdot t_{\text{on}})}$, where $t_{\text{on}}$ is the resolution of the TDC.
B. PLL Tracking

Since acquiring samples (which involves lighting an LED) is the most power intensive part of gathering a plethysmogram, one way to reduce power is to reduce the duration for which the LED is turned ON for each measurement, as discussed in the previous sections. Another approach to reducing power is to take fewer samples which translates into turning ON the LED fewer times on average.

The samples that are actually useful in computing SpO₂ are those at the peaks and troughs of the photoplethysmogram. So, if we can estimate when these peaks and troughs are likely to happen, sampling can be performed only just before the time when these events are expected to occur. Since this is similar to the way a PLL works, we call this technique “PLL tracking”. We emphasize that this kind of non-uniform sampling is possible only because our photodetector architecture does not have a band pass filter in the pipeline.

We implemented this technique, wherein after detecting the occurrence of a peak in the photoplethysmogram, the system skips sampling for a duration equal to 50% of the expected peak-to-peak interval.

However, this technique is not without issues. The heart rate can vary considerably from one cycle to the other. So, it is possible for the loop to lock on to a fraction of the heart rate, which results in misreporting of the heart rate. To prevent this from happening for a prolonged duration, we reset the loop once every 10 cycles and force it to “re-lock”. Hence, it takes much longer to be confident of heart rate measurements. Moreover, with this technique, a record of the complete plethysmogram is not kept. So, the care-giver cannot visualize the plethysmogram. Therefore, this approach is suitable when the power budget is aggressive and the entire plethysmogram is not desired.

A flowchart describing both the “Minimum SNR tracking” and “PLL tracking” techniques is shown in Fig. 11. To detect the peaks, we used a time-domain window based peak detector. The amplitude of the edge in the window is tracked once it exceeds a certain threshold. After the peak passes, the amplitude in the window starts to fall. At this point we declare that a peak has been found, and the detection threshold is reset to be a fraction of the most recently observed peak amplitude. This threshold is then gradually reduced over time so that smaller peaks, if they occur in the future, are accepted. However, the power reduction methods discussed in this paper do not solely rely on this particular peak detection algorithm, and other methods, such as template matching, may also be used.

V. EXPERIMENTAL RESULTS

A prototype was built using CC2540, a low power platform from Texas Instruments. The Bluetooth Low Energy (BLE) radio was disabled, and the timer peripheral on the SoC was used as the time-to-digital converter (TDC). The fingertip probe used was a ChoiceMMed MD2000B. The other components used in the prototype referenced in Fig. 1 are detailed in Table II.

A representative photoplethysmogram from the prototype oximeter is shown in Fig. 12. Plotted on the vertical axis are measurements made by the TDC in Fig. 1. We chose the sample rate for each channel (red or IR) to be 100 Hz because it allows us to easily suppress the 50 Hz power line interference with a 2-point FIR low-pass filter. First, the control algorithm recognizes that the SNR of the acquired plethysmogram is higher than necessary, and the step like reduction indicates the decrease in LED on-time (increase in the gain of the second stage in Fig. 1). Second, the “PLL tracking” algorithm skips samples between peaks. After the reduction of LED on-time, the “PLL tracker” is reset, and then it “re-locks” to the heart rate.

In our tests, the “Minimum SNR tracking” loop settled to a steady state within 25 seconds after the finger is inserted into the probe. This is acceptable because we expect this to be used when SpO₂ is remotely monitored continuously for hours at a time. Furthermore, since each peak-trough measurement is tagged with SNR, SpO₂ can be confidently measured even if the loop is not in steady state.

3The real-time plotting tool we developed is available under an open source license at https://github.com/s-gv/stream-plot.
TABLE II
COMPONENTS USED IN THE PROTOTYPE

<table>
<thead>
<tr>
<th>Component</th>
<th>Part Used</th>
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</thead>
<tbody>
<tr>
<td>Opamps</td>
<td>OPA2314</td>
</tr>
<tr>
<td>Comparators</td>
<td>TLV3202</td>
</tr>
<tr>
<td>Reference generators (V_{r1}, V_{r2})</td>
<td>REF3312, REF3325</td>
</tr>
<tr>
<td>Switch (S1)</td>
<td>MAX4594</td>
</tr>
<tr>
<td>Power Gate</td>
<td>TS3A4751</td>
</tr>
<tr>
<td>Digital Potentiometer (\text{gain } A)</td>
<td>TPL0501-100</td>
</tr>
<tr>
<td>C (integration capacitor)</td>
<td>100 pF Timer1 (16-bit) of CC2540</td>
</tr>
</tbody>
</table>

Fig. 12. A photoplethysmogram from the proposed pulse oximeter. The vertical axis is normalized to 31.25 μs.

A. Calibration and Accuracy

We calibrated the prototype using finger simulators from BC Biomedical group. The finger simulators had known \(\text{SpO}_2\) levels of 80%, 90%, and 97%. Performing linear regression on the acquired readings gave \(a = 112.8\) and \(b = 24\) in (5).

Accuracy of the proposed oximeter was verified by comparing the readings from the proposed oximeter with readings from a commercial fingertip oximeter ChoiceMMed MD300C2D. The accuracy test was performed on 10 adults. Among the 10 volunteers, the highest measured \(\text{SpO}_2\) was 99% and the lowest was 93%. In 9 cases, the difference between reported \(\text{SpO}_2\) readings from the prototype oximeter and the commercial oximeter was no more than 1%. In one case, the difference was 2%.

B. Impact of Motion Artifacts

One of the issues with pulse oximetry is that it is difficult to obtain \(\text{SpO}_2\) readings when there is relative motion between the probe and the body. Techniques to alleviate this have been proposed in [34], [35]. While those techniques cannot be directly applied to our system, we demonstrate that the power reduction techniques we have described in this paper are themselves resistant to occasional motion artifacts. However, similar to a conventional oximeter, the proposed power optimized oximeter is still vulnerable to motion artifacts.

We argue that motion artifacts will not deteriorate the performance of “Minimum SNR tracking”. To reduce chances of motion artifacts affecting signal level measurement, the signal level from the past 5 peaks is averaged after removing the maximum and minimum signal level, and then SNR is computed. In the event that an erroneous signal level measurement creeps in through this check, one of two things can happen: either the SNR is underestimated or it is overestimated. If the SNR is underestimated, the loop increases the measurement duration and burns more power for a while before reducing the measurement duration. In this case, the readings are unaffected, and the only impact is that the system burns higher power than necessary for a short while. On the other hand, if the SNR is overestimated, the loop reduces the measurement duration, and the SNR of the acquired readings will be lower than acceptable. Because each signal measurement is tagged with SNR, those readings with below acceptable SNR get rejected and are not reported to the user. After detecting that the SNR is lower than necessary, the measurement duration is increased. A sample waveform where the loop erroneously chooses a lower than acceptable LED ON-time because of motion artifacts and then recovers after the transient artifact has passed, is shown in Fig. 13. Since \(\text{SpO}_2\) changes relatively slowly, the occasional loss of readings will not affect system operation. Furthermore, it is possible to avoid even this if we are willing to burn slightly more power by setting the target SNR of the loop to be slightly higher than the minimum required SNR. Then, even if the loop occasionally acquires readings at SNR levels below its target, the SNR still remains higher than what is necessary, and the readings continue to be valid. The fact that motion artifacts are transient, coupled with the constant step approach to changing the measurement duration, reduces the impact of such artifacts.

The “PLL tracking” algorithm is also affected by motion artifacts, but in a more benign manner. The rapid occurrence of edge-like features in the plethysmogram during motion artifacts can cause the “PLL tracking” algorithm to underestimate the peak to peak interval. Once the transient artifact has passed, the tracking algorithm, which now expects a short peak to peak interval, waits until the next peak due to a heartbeat and “relock” to the heart rate. A recording that demonstrates this is shown in Fig. 14. Even in the extraordinary event that the motion artifact causes the algorithm to lock onto an integral fraction of the heart rate, the duration for which the heart rate is misreported is controlled. This is because the tracking loop is forced to re-lock once every 10 cycles. The output of the heart rate from this
scheme has to be inspected and cleaned (for example, using a median filter) before reporting the heart rate to the user.

C. Power Consumption

Power consumption was measured using Agilent source measurement unit U2722A. The microcontroller and the analog components were powered by separate channels, and the power for each was thus measured. The LEDs were powered from the microcontroller IO pins. Since we measured the duration for which the LEDs were powered, and the LED current was kept at a fixed level (about 5 mA for the red LED and 7 mA for the IR LED), we could compute the LED power and subtract it from the total power consumed by the microcontroller to separate LED power from processing power.

The plot in Fig. 15 shows the impact of each of the proposed dynamic adaptation techniques and also how they work in tandem to reduce power. Analog power is the total power consumed by the analog parts of the system, which includes opamps, comparators, and reference generators. Processor power refers to the power consumed by the digital parts of the oximeter, which includes the power consumed by the TDC, the oscillator for the system clock, and the processor (which runs control algorithms and calculates SpO2, heart rate from the samples). The power for the entire platform, with the exception of the radio (which is turned OFF), is reported. All the elements of the platform including analog circuitry, TDC, processor, and the system clock generator, with the exception of the 32 kHz sleep timer, are duty cycled.

A constraint posed by the CC2540 platform is that the processor core has to be active when the timer, which we employ as a TDC, is enabled. So, when “Minimum SNR” tracking is enabled, and the LED ON-time reduces, the fraction of the time for which the entire platform is active also reduces. Hence, the processor power reduces. Similarly, when “PLL” tracking is enabled, the entire platform, again with the exception of the 32 kHz sleep timer, sleeps for about 0.5 seconds when samples are skipped, and thus the average power goes down. Using “PLL tracking” cuts the number of samples acquired by 35%, and as we expected, the power consumption gets cut by the same percentage.

Table III compares the power consumption of the proposed design with other implementations. The power reported is the total power consumption of the platform which includes LED power, analog power, and the power consumed by the processor. Data for commercial oximeters was obtained from [19]. This comparison only serves to show that our implementation is competitive because the absolute numbers are dependent on the probe characteristics. Finally, assuming that “PLL tracking” is completely ineffective and that the LED ON-time is at its maximum value of 2 ms (the TDC in our implementation overflows at 2 ms), the estimated worst-case power consumption of our prototype is about 16 mW.

VI. CONCLUSION

Remotely sensing physiological parameters could reduce mortality while lowering the cost of health care, and low-power sensors are essential for remote sensing. We have presented a novel low-power pulse oximeter. In pulse oximetry, acquiring
samples is expensive in terms of power because of the need to light an LED during sampling. Design-space analysis was performed to explore the trade-off between spending power in the LED and burning power in a higher performance amplifier. However, designing for the worst-case results in excessive power consumption in most situations. We showed that dynamic adaptation techniques lower power considerably by operating the sensor at the edge of the SNR requirement and acquiring samples only when necessary.

**APPENDIX A**

**PERFUSION IN TERMS OF TDC MEASUREMENTS**

The peak and trough of the TDC measurements in Fig. 1 may be written as

\[
t_{\text{tdc(peak)}} = \frac{C \delta V_r}{AI_{pd(\text{peak})}}
\]

and

\[
t_{\text{tdc(trough)}} = \frac{C \delta V_r}{AI_{pd(\text{peak})}} I_{pd(\text{ac})}
\]

where \( I_{pd(\text{peak})} \) and \( I_{pd(\text{tough})} \) correspond to the peak and trough of the photocurrent (see Fig. 3). Thus

\[
\begin{align*}
 t_{\text{tdc(peak)}} & = \frac{C \delta V_r}{AI_{pd(\text{peak})} I_{pd(\text{ac})}} \\
 t_{\text{tdc(trough)}} & = \frac{C \delta V_r}{AI_{pd(\text{peak})} I_{pd(\text{tough})}}
\end{align*}
\]

(22)

(23)

where \( I_{pd(\text{ac})} \) is \( I_{pd(\text{peak})} - I_{pd(\text{tough})} \) and \( I_{pd(\text{dc})} \) is \( (I_{pd(\text{peak})} + I_{pd(\text{tough})})/2 \). From (22) and (23), the perfusion \( P \) is

\[
P = \frac{I_{pd(\text{ac})}}{I_{pd(\text{dc})}} = \frac{t_{\text{tdc(peak)}}}{t_{\text{tdc(dc)}}}.
\]

(24)

Thus, the perfusion computed from TDC measurements is equal that computed from the photocurrent measurements.

**APPENDIX B**

**NOISE ANALYSIS OF THE PHOTODIODE INTERFACE CIRCUIT**

In this section, we analyze the noise performance of the switched integrator and derive (14). The ramp that is fed to the comparator may be written as

\[
V_0(t) = A \frac{C}{I_{\text{pd}}} \int_0^t (I_{\text{pd}} + i_n(\tau)) d\tau + Av_n(t)
\]

(25)

where \( i_n \) is the photodiode noise current and \( v_n \) is the voltage noise due to the opamp voltage noise. Substituting \( t = t_{\text{r1}} \) and \( t = t_{\text{r2}} \) and subtracting

\[
\begin{align*}
V_{r2} - V_{r1} &= \frac{AI_{pd}}{C} \left( t_{\text{r2}} - t_{\text{r1}} \right) + A \int_0^{t_{\text{r2}}} i_n(\tau) d\tau \\
&\quad - A \int_0^{t_{\text{r1}}} i_n(\tau) d\tau + A(v_n(t_{\text{r2}}) - v_n(t_{\text{r1}}))
\end{align*}
\]

(26)

Substituting \( t_{\text{tdc}} = t_{\beta} - t_{\text{r1}} \) from (8)

\[
\begin{align*}
V_{r2} - V_{r1} &= \frac{AI_{pd}}{C} t_{\text{tdc}} \\
&= \frac{V_{r2} - V_{r1}}{\frac{A I_{pd}}{C}}.
\end{align*}
\]

(27)

Re-arranging (26), squaring, and taking expectation

\[
E \left[ (V_{r2} - V_{r1} - \frac{AI_{pd}}{C} t_{\text{tdc}})^2 \right] = E \left[ \frac{A^2}{C^2} \int_0^{t_{\text{r2}}} i_n(\tau) d\tau \\
- A \int_0^{t_{\text{r1}}} i_n(\tau) d\tau + A(v_n(t_{\text{r2}}) - v_n(t_{\text{r1}}))^2 \right].
\]

(28)

Since the photodiode noise and opamp noise are uncorrelated, the chain rule for expectations can be used to obtain

\[
\begin{align*}
(V_{r2} - V_{r1})^2 + \frac{A^2 I_{pd}^2}{C^2} E \left[ t_{\text{tdc}}^2 \right] - \frac{2AI_{pd}}{C} E \int_0^{t_{\text{r2}}} i_n(\tau) d\tau \\
&\quad - \frac{A^2}{C^2} E \left[ \int_0^{t_{\text{r1}}} i_n(\tau) d\tau \int_0^{t_{\text{r2}}} i_n(\tau) d\tau \right] = 2A^2 \sigma_n^2
\end{align*}
\]

(29)

Substituting for \( E[t_{\text{tdc}}] \) from (27)

\[
\begin{align*}
\frac{A^2 I_{pd}^2}{C^2} E \left[ t_{\text{tdc}}^2 \right] &= (V_{r2} - V_{r1})^2 + \frac{2A^2 \sigma_n^2}{C^2} + \frac{A^2 \sigma_{\text{in}}^2}{C^2} E[t_{\text{tdc}}].
\end{align*}
\]

(30)

Since \( \sigma_{t_{\text{tdc}}}^2 = E[t_{\text{tdc}}^2] - E[t_{\text{tdc}}]^2 \) and \( \sigma_n^2 = v_{\text{in,n}}^2 A_N^2 \omega_n b \),

\[
\sigma_{t_{\text{tdc}}}^2 = \frac{2v_{\text{in,n}}^2 A_N^2 \omega_n b}{C^2} + \left( \frac{I_{\text{pd}}}{C} \right)^2 E[t_{\text{tdc}}].
\]

(31)

Substituting this in (10)

\[
\text{SNR}^2 = \frac{I_{\text{pd}}^2}{A^2 \left( \frac{2v_{\text{in,n}}^2 A_N^2 \omega_n b}{C^2} \right)^2 + A \left( \frac{I_{\text{pd}}}{C} \right)^2 E[t_{\text{tdc}}]}
\]

(32)

Re-arranging terms in (31), using (10), and setting \( A = 1 \)

\[
\begin{align*}
v_{\text{in,n}}^2 &= \frac{1}{2A_N^2 \omega_n b} \left[ \left( \frac{I_{\text{pd}}}{C} t_{\text{tdc(peak)}} \right)^2 - \left( \frac{I_{\text{pd}}}{C} t_{\text{tdc(dc)}} \right)^2 \right].
\end{align*}
\]

(33)
From (8) and (12)

\[ t_{td,\text{fr}}(\delta) = \frac{\delta V_r}{V_2^2} t_{\text{inv}(\text{avg})}. \]  

(34)

Substituting this into (33) and using (9), the maximum permissible input referred noise spectral density is

\[ v_{\text{in},n}^2 = \frac{\delta V_r^2}{2A_N^2 C^2 V_r \omega_n} \left[ \frac{P^2 \delta V_r \text{ton(avg)}}{\text{SNR}_V V_r^2} \right] \left( \frac{\omega_n^2}{\omega_d^2} \right) \]  

(35)

ACKNOWLEDGMENT

The authors would like to thank Manikandan, Viveka, and Pushkar for their suggestions and Hitesh for assisting with the CC2540 platform. They also thank the anonymous reviewers for their comments, and acknowledge the volunteers who participated in this research. Signed consent was obtained from these volunteers on a less-than-minimum-risk consent form which described the experiment and informed participants that we would not disclose any personally identifiable data and that their participation or their refusal to participate in the research at any point in time would in no way affect their privileges at the institute or their professional relationship with the investigators.

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