Dynamic Slope Detection: A High-Compression Fidelity-Preserving Approach for ECG Signal Acquisition

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***Abstract*—This paper introduces a novel Dynamic Slope Detection (DSD) system for acquiring electrocardiogram (ECG) signals. DSD addresses the critical challenge of balancing data storage requirements with signal fidelity, particularly in resource-constrained environments like wearable devices. The system leverages the slope information of the ECG signal to guide efficient and adaptive data sampling. Validation using ten samples from the publicly available MIT-BIH Arrhythmia Database confirmed significant data reduction compared to traditional sampling. The proposed method achieves a compression ratio of up to $12.5\times$ while maintaining RR interval estimation error below ± 0.1 msec.**

***Index Terms*—Electrocardiogram (ECG), analog-to-digital converter (ADC), low-power circuits, slope level-crossing sampling, and wearable devices.**

I. INTRODUCTION

As wearable health devices become ubiquitous, a critical need arises for signal processing and transmission techniques that minimize power consumption and memory usage. Conventional sampling and signal processing occur at a fixed, worst-case sampling rate dictated by the Nyquist-Shannon theorem [1]. Biomedical signals such as ECG often show temporal variations in their spectral properties [2]. In addition, a fixed sampling rate leads to unnecessary wasted samples and energy during processing, transmission, and reception. Consequently, reducing memory requirements in portable medical systems is vital for storing more points, allowing longer-term monitoring.

Timely diagnosis and treatment of cardiovascular diseases (CVD) can significantly mitigate health deterioration caused by these conditions. Real-time heart monitoring is a crucial strength of wearable devices, offering continuous data collection with high clinical insight [3]. These systems favor on-sensor processing over directly transmitting raw data to the cloud due to latency, security, privacy concerns, and power consumption [4]. This prioritization of on-sensor processing allows for diverse applications, such as transmitting extracted critical information to healthcare professionals or enabling on-sensor automatic arrhythmia classification using Machine Learning (ML) algorithms [5].

Event-driven processing, exploiting level-crossing (LC) techniques, offers an attractive alternative to traditional sampling, significantly reducing data sets [6]–[8]. However, most of the current approaches lack precision in locating turning points (fiducial points) due to significant gaps [6], require necessary post-processing to detect waveform characteristics, and may generate redundant samples in high-amplitude and low-frequency signals [8], [9]. While post-ADC compression can address this, it increases energy and storage demands.

This paper proposes a novel dynamic slope detection method for ECG monitoring and detection on-device. Inspired by the Address Event Representation (AER) event-driven communication protocol used in image sensors [10] and particle detection [11], our approach offers an efficient alternative to traditional fixed-rate sampling and computationally expensive level-crossing methods. By leveraging real-time information about signal turning points and dynamics, our method facilitates efficient ECG data acquisition, low memory usage, and reliable transition detection for fiducial points directly on wearable devices. This capability empowers wearable ECG monitoring with significant reductions in data volume and enhanced on-device processing capabilities.

II. CIRCUIT AND SYSTEM DESIGN

Figure 1 shows the proposed system. It consists of a discrete differentiator circuit [12], followed by dual comparators with dynamically adjustable thresholds V_{thp} and V_{thn} controlled by digital-to-analog converters (DACs). These comparators enable configurable detection of positive and negative slopes in the ECG signal V_{in}. Finally, a slope controller implemented within a Field-Programmable Gate Array (FPGA) generates ADC's control signal start-of-conversion (SoC) based on the input signal and the current state.

An additional set of RC (Resistor + Capacitor) was incorporated to differentiate the signal. This introduces a high-frequency roll-off, reducing gain at higher frequencies and improving circuit noise rejection and stability. The output of the differentiator circuit can be described in terms of the

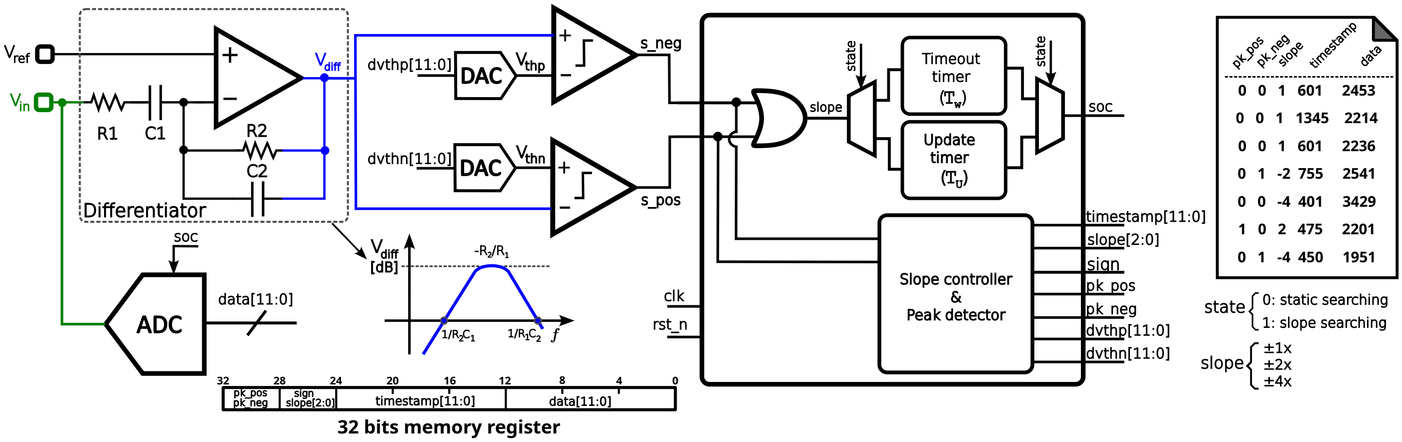

Fig. 1. Block diagram of the proposed approach, including a differentiator circuit made of one OPAMP, resistors (R_1=36 $k\Omega$, R_2=390 $k\Omega$) and capacitors (C_1=47 nF, C_2=4.7 nF), two DACs, an analog-to-digital converter (ADC), and a digital slope controller embedded in FPGA.

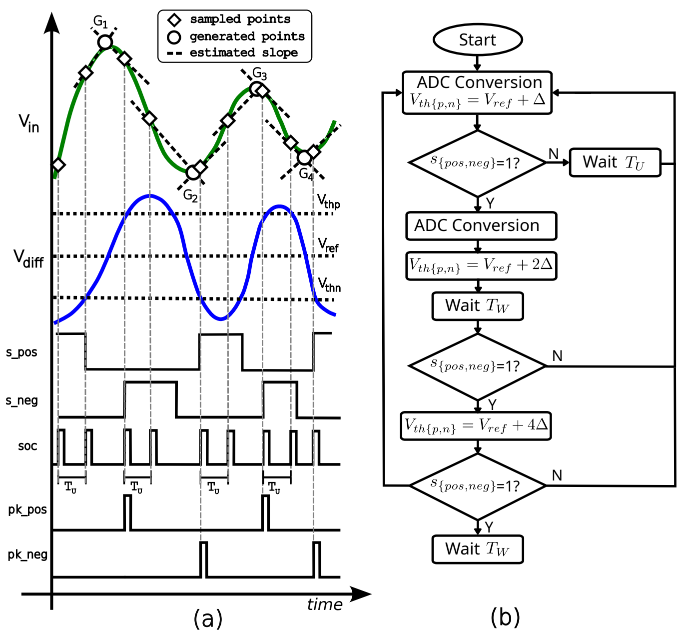

Fig. 2. (a) Waveforms representing the operation in SSD mode for the circuit in Figure 1. (b) Flowchart for the DSD method.

resistors (R_1 and R_2) and capacitors (C_1 and C_2) by the following equation:

$$V_{diff} = -\left(\frac{R_2}{R_1}\right)\frac{dV_{in}}{dt} \quad (1)$$

The minimum slope signal that triggers the comparators outputs *s_neg* and *s_pos* can be defined as:

$$Slope_{min\{p,n\}} = \Delta V_{th\{p,n\}}\left(\frac{R_1}{R_2}\right) \quad (2)$$

where $\Delta V_{th_p} = V_{th_p} - V_{ref}$ and $\Delta V_{th_n} = V_{th_n} - V_{ref}$. In this work, we employ a symmetric threshold difference, denoted by ΔV_{th}, for both positive and negative peaks.

The system operates in two distinct modes:

1) **Static Slope Detection (SSD):** In this mode, the system continuously monitors the ECG signal for slope changes that exceed the minimum threshold $Slope_{min_{p,n}}$. When a new crossing (transition point) is detected, the signal *SoC* (start-of-conversion) is asserted, as is shown in Figure 2. This assertion initiates a new ADC conversion process. Meanwhile, a timer is activated and counting until a predefined update time, T_U, is reached if the dynamic condition persists. Then, a new conversion begins, and the value is updated. Furthermore, a new conversion is started if no new zero-crossing is detected within the timeframe of T_O greater than T_U. This approach ensures a minimum sampling rate even in low-activity ECG segments.
2) **Dynamic Slope Detection (DSD):** In DSD mode, the system behavior is dynamic and adapts to the incoming ECG signal. A conversion is initiated upon detecting a significant change or minimum slope, and then the threshold voltage difference (ΔV_{th}) is doubled. If the change persists (refer to the flowchart in Figure 2(b) for details), ΔV_{th} is further doubled. However, if either a slope event is not detected or the slope condition no longer holds, the last slope value is stored, and a counter is activated. This counter increments until it reaches a predefined wait time, T_W. In the absence of sustained changes, the system reverts to behaving like the SSD mode.

The system identifies positive and negative peak events by analyzing the sequence of trigger events. A positive peak is detected when a negative-going trigger follows a positive-going trigger. Conversely, a negative peak is identified by a positive-going trigger followed by a negative-going trigger, as shown in Figure 2 (a). Even if the actual peak is not directly sampled, the system can still estimate the peak value and time of occurrence. This estimation is possible by leveraging the information from the slope data and timestamps. The steepness information provides insight into the rapid changes around the peak, and the timestamps pinpoint the window

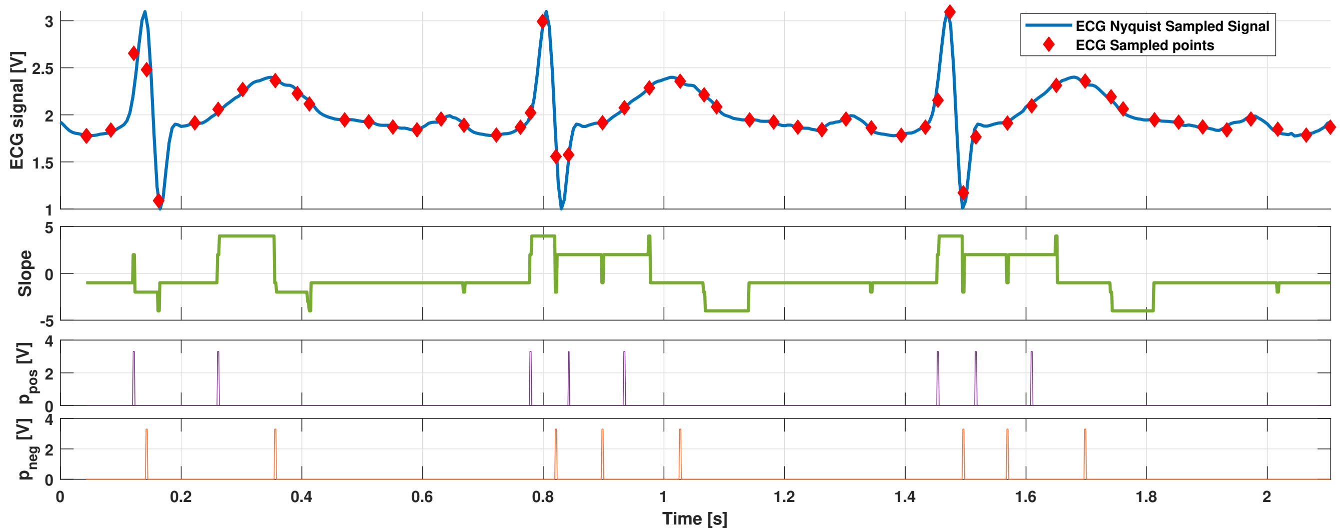

Fig. 3. Measured results: Blue trace represents the ECG sampled at Nyquist frequency (f_N), and the red dots are the sampling points using DSD with T_U = 20 ms, T_W = 40 ms). The green curve is the DSD slope signal (guides efficient sampling). Positive/negative pulses are generated based on the slope information.

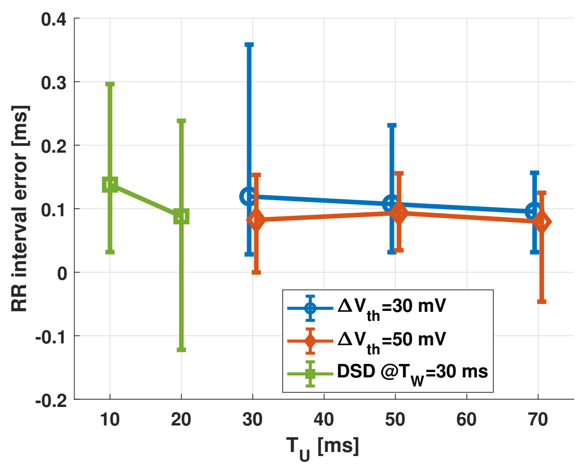

Fig. 4. Comparison of RR interval error in time between the proposed method and Nyquist sampled ECG vs. update time T_U using ten datasets from the MIT-BIH Arrhythmia database [13].

where the peak likely resides. The system can achieve efficient peak estimation by utilizing these elements without complex divisions or further digital processing.

By capturing significant changes at different sensitivity levels ($1\times$, $2\times$, and $4\times$), DSD can effectively differentiate between the P-wave (often having a lower slope), the QRS complex (characterized by a larger and steeper slope), and the T-wave (typically with a smaller slope compared to the QRS).

The DSD's output is a 32-bit per sample dataset containing the timestamp and sampled points, as well as the slope and the positive or negative peak detection (See Figure 1).

III. Results and Discussion

The proposed system was implemented and tested using readily available, off-the-shelf electronic components. An Opal Kelly XEM 7310MT board served as the digital controller. This board features a Xilinx Artix-7 Field-Programmable Gate Array (FPGA). A 12-bit DAC 124S085 handled the digital-to-analog conversion, while a Texas Instruments ADC78H90 (12-bit, 500 kS/s) performed the analog-to-digital conversion. An MCP6004 operational amplifier (Op-Amp) played a role in the differentiator circuit.

The system's clock period is 50 µs, defining the maximum resolution for timing calculations, including the signal turning points and counter ticks. Ten ECG signals were selected to test the approach from the MIT-BIH Arrhythmia Database available in [13]. These ECG signals were loaded onto a Keysight EDU33212A Waveform Generator using 1 V_{pp}. Most comparisons were based on the same ECG dataset sampled at the Nyquist frequency ($f_n = 200$ Hz), named here as the reference signal.

Figure 3 illustrates the performance of the Dynamic Slope Detection (DSD) systems compared to traditional Nyquist-rate sampling for ECG acquisition. Figure 4 shows the mean, maximum, and minimum error of the estimated RR interval compared with this reference signal. The RR interval, the time between consecutive R peaks in the ECG, determines the heart rate (beats per minute). By comparing the estimated RR intervals with the reference, we can evaluate the accuracy of the system's peak detection and timing estimation capabilities. Figure 5 represents the downsampling ratio achieved by the DSD and SSD system compared to the reference signal. A downsampling ratio of 2 indicates that the DSD system acquires data points at half the rate of the Nyquist frequency. Higher ratios signify even more significant data reduction

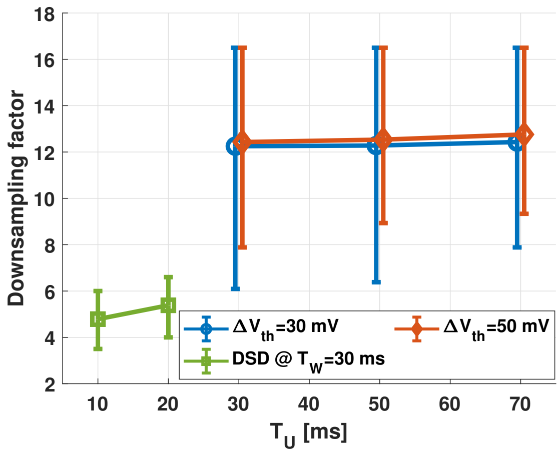

Fig. 5. Downsampling ratio achieved by the proposed method compared to a Nyquist-sampled ECG signal vs. update time T_U using ten datasets from the MIT-BIH Arrhythmia database [13].

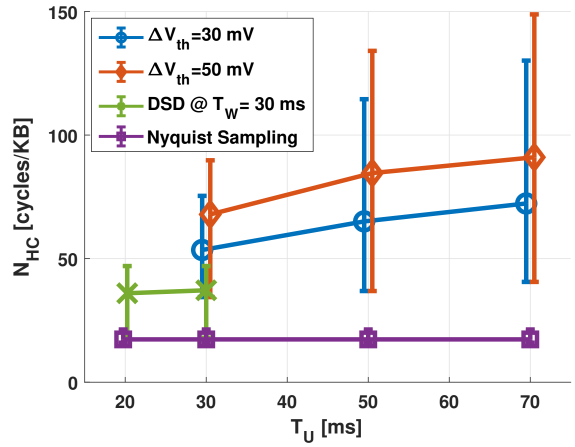

Fig. 6. Number of heart cycles (N_{HC}) stored in a 1 kB memory device using our method compared to a Nyquist-sampled ECG signal vs. update time T_U and based on ten datasets from the MIT-BIH Arrhythmia database [13].

TABLE I
COMPARATIVE ANALYSIS OF STATE-OF-THE-ART APPROACHES.

	This work	[8]	[14]	[15]
Method	DSD	2n Order LC-ADC	Signal-dependent	Slope Level Crossing
Turning point detection	Yes	Yes	Yes	Yes
Sampling rate	Async.	1 kHz	1 kHz	1 kHz
Resolution	12 bits	10 bits	12 bits	10 bits
Compression factor	5.38 @DSD 12.53 @SSD	8.33	6.1	6.17
System implementation	Off-the Shelf Components	Integrated Circuit	Integrated Circuit	Off-the-Shelf Components

and lower ADC power consumption. Figure 6 showcases the potential memory savings achieved by the proposed techniques, showing a trend where the number of storable heart cycles (N_{HC}) increases with increasing update time (T_U). The SSD/DSD system acquires data points with higher TU values less frequently, leading to longer heart cycle recordings.

This work is compared to other state-of-the-art methods for acquiring ECG signals in Table I.

Our approach offers a better alternative to traditional methods, such as 2^{nd} order LC or Slope-Level Crossing (SLC) techniques, which rely on fixed sampling rates. With DSD, we can dynamically adjust the sampling rate based on the slope information of the signal. This results in similar signal fidelity, including accurate turning point detection and RR interval estimation, while achieving a higher compression ratio of 12.53. DSD requires less storage space and may have a more straightforward implementation using readily available components.

IV. CONCLUSIONS

This work presented a novel Dynamic Slope Detection (DSD) system for ECG signal acquisition. The system utilizes slope information to guide efficient, adaptive data sampling, significantly reducing the number of acquired data points compared to traditional Nyquist-rate approaches. This strategy demonstrably leads to a compression ratio of 12.53, making DSD suitable for applications with limited storage resources, such as wearable ECG devices. The DSD system's update time (T_U) parameter allows users to fine-tune the balance between data reduction and the amount of ECG signal information captured, making it relevant to other applications. Overall, the DSD system presents a compelling approach for ECG signal acquisition, offering efficient data acquisition, preserved signal fidelity, and the ability to optimize for specific application needs. Future work may explore integrating DSD with ML algorithms for enhanced analysis and real-time health monitoring applications.

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