

Low-Power Real-Time ECG Baseline Wander Removal: Hardware Implementation

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Abstract—This paper presents a hardware realisation of a novel ECG baseline drift removal that preserves the ECG signal integrity. The microcontroller implementation detects the fiducial markers of the ECG signal and the baseline wander estimation is achieved through a weighted piecewise linear interpolation. This estimated drift is then removed to recover a “clean” ECG signal without significantly distorting the ST segment. Experimental results using real data from the MIT-BIH Arrhythmia Database (recording 100 and 101) with added baseline wander (BWM1) from the MIT-BIH Noise Stress Database show an average root mean square error of $34.3 \mu\text{V}$ (mean), $30.4 \mu\text{V}$ (median) and $18.4 \mu\text{V}$ (standard deviation) per heart beat.

I. INTRODUCTION

Electrocardiography (ECG) is the main diagnostic tool for detecting cardiac disorders using electrodes positioned on the chest to measure and interpret the activity of the heart. This non-invasive procedure can provide crucial information for clinicians. According to the World Health Organization, cardiovascular related diseases (CVDs) are still the main cause of deaths globally [1]. In 2012, 31 % of all deaths (≈ 17.5 million) were related to CVDs, the primary causes being coronary heart disease (≈ 7.3 million) and stroke (≈ 6.2 million) [2]. It is predicted that in the year 2030, 23.3 million people will die due to cardiovascular-related diseases and that it will remain the single leading cause of death [3].

ECG’s non-invasiveness coupled with the growing trend in wearable, ambulatory systems has given it a resurgence in sports and healthcare alike. However, critical challenges in ambulatory monitoring still exist to maintain “clean” ECG signal without compromising the clinical validity of the ECG.

One feature in particular that is highly sensitive to noise and distortion is the ST segment of the ECG as shown in Fig. 1. The American Heart Association (AHA) and International Electrotechnical Commission (IEC) standards indicate that a $100 \mu\text{V}$ elevation/depression in the ST segment can be an indicator of myocardial infarction, commonly known as *heart attack* [4]. Such a condition occurs when coronary arteries are occluded due to an unstable build-up of white blood cells, cholesterol and fat, causing oxygen deprivation in the heart tissue.

Removal of the noise artefacts and interference poses significant challenges to obtain clinically valid ECG data. As the spectral content of the noise sources falls into the ECG bandwidth (0.05 - 150 Hz) and is comparable in amplitude (2 - 3 mV), frequency-based removal techniques often distort the signal of interest. For this reason, the AHA limits the high-pass cut-off frequency of such systems to 0.05 and 0.67 Hz for filters with phase and non-phase distortion respectively [4].

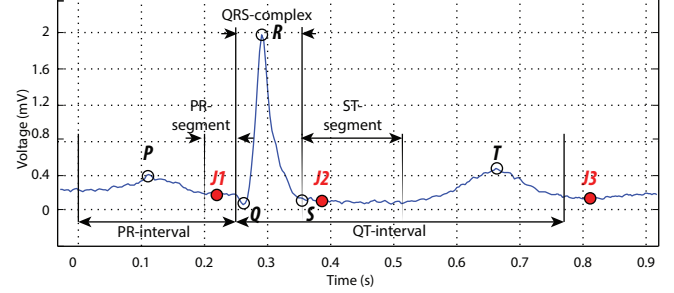


Fig. 1. Typical ECG waveform showing key features and fiducial points (J1-3) used to track the baseline wander [5].

The noise sources and the signal processing techniques to remove the baseline wander were discussed in our previous work [5]. Hardware realisations of several methods to remove baseline wander based on digital signal processors (DSPs), microcontroller units (MCUs) and field-programmable gate arrays (FPGAs) have been reported in the literature [6]–[9].

This paper focuses on the embedded system realisation of the developed baseline wander (BW) removal algorithms for real-time ambulatory monitoring. Section II gives a brief introduction on the developed algorithms; Section III describes the embedded system structure and methodology; Section IV details the datasets used in testing and the data type; Section V presents the results acquired in an embedded target (TI MSP430); and Section VI concludes the paper.

II. ALGORITHMIC APPROACH

An efficient MCU-based implementation is made possible through our past works that have developed computationally-efficient algorithms to estimate the ECG baseline wander. These approaches provide a robust method for ECG signal integrity in baseline wander removal and will be described in the following sections.

A. Baseline Wander Estimation

Baseline wander estimation algorithm initially downsamples the ECG signal and crudely removes the noise interferences through filtering. In order to track the baseline wander, three fiducial (J1-3) points per ECG heart beat are then detected as fiducial markers. These points (illustrated in Fig. 1) are located within the PR segment, ST segment and after the QT interval. Once these points are successfully located and their elevation differences are compensated, baseline wander is estimated through spline interpolation and subtracted from the

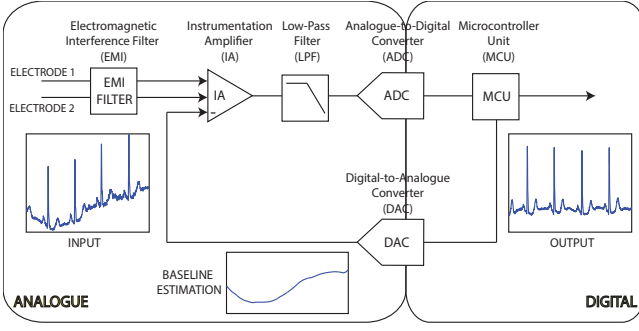


Fig. 2. ECG baseline wander removal system architecture.

raw ECG data. The detailed operation of the baseline wander estimation algorithm is explained in our previous work [5].

B. Weighted Piecewise Linear Interpolation

The computational complexity of the spline interpolation algorithms utilised in baseline wander estimation algorithm forms a bottleneck in real-time hardware realisation. Therefore, weighted piecewise interpolation (WPL) aims to lower the computational complexity of the overall system.

The algorithm divides each spline segment defined by the two consecutive fiducial points into subsections and utilises slope calculations of the current and previous spline segments to interpolate each subsections separately. This hybrid approach yields higher accuracy than linear interpolation and requires less computational complexity compared to its polynomial counterparts. The detailed operation of WPL interpolation algorithm is explained in our other paper [10].

III. SYSTEM IMPLEMENTATION

The overall system architecture of the low-power real-time ECG baseline wander removal hardware is illustrated in Fig. 2. The individual processes with the indicative signals at each point through the datapath are also demonstrated in the same figure.

The DC-coupled approach with the instrumentation amplifier at the front end suppresses common mode noise and amplifies the input to utilise the full dynamic range of the analogue to digital converter (ADC). Following that, an analogue anti-aliasing filter rejects the frequency content above 150Hz and the ADC digitises the ECG signal with the noise artefacts present. The low-frequency noise interferences are then estimated in the digital domain and subtracted from the input to obtain a “clean” ECG signal. This processing is acquired in a microcontroller unit (MCU) and the implementation methodology of the previously discussed algorithms is covered in this section.

A. Biquad Filter Implementation

In baseline wander detection algorithm, the total number of multiplication operations are reduced by replacing IIR filters with FIR filter implementations for the high-pass and low-pass filters. These filters crudely remove noise artefacts in the digital domain so that fiducial markers can be estimated accurately.

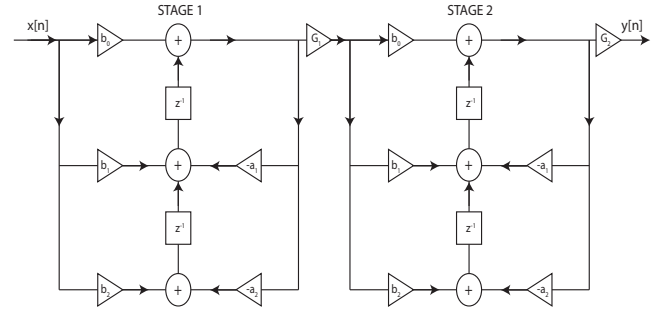


Fig. 3. Transposed-direct-form II of two stage biquad filters.

The IIR filters are implemented in the MCU as two biquad filters in transposed-direct form II as shown in Fig. 3. These type of filters are a second-order recursive linear filter with two poles and zeros. Eq. 1 shows the transfer function of such filters, where the feed-forward coefficients are denoted with b_0 , b_1 and b_2 , the feedback path coefficients with a_0 , a_1 and a_2 , and the gain with G . Such direct-form II implementations save two extra memory locations and the intermediate sums are achieved with close-valued numbers achieving higher precision.

$$H(z) = G * \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \quad (1)$$

B. Buffer Implementation

The microcontroller implementation is designed to operate in a serial-in, serial-out format. As the fiducial points are non-uniformly located, any duration increase between two consecutive fiducial points stalls the microcontroller operation. These instances occur during large step changes, missing QRS complexes, and/or changes in the heart beat rate. Therefore, a buffer implementation is required. This way, an interpolated output of the baseline estimation for every sampled ECG input is guaranteed by storing the location of detected fiducial points in the buffer at the start-up.

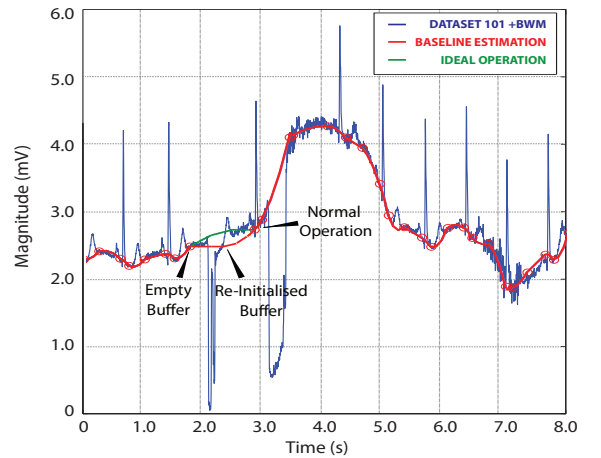


Fig. 4. Buffer re-initialisation of the interpolation algorithm.

In cases where the buffer is processed completely, the overall algorithm is put into the buffering process and the interpolation re-starts once enough number of fiducial points are located. Fig. 4 demonstrates such an operation where the buffer is emptied at the 1.8 second mark and the interpolation output stalls for certain period of time as shown with red. The same figure also shows the ideal interpolation with green. After the re-initialisation, the algorithm recovers and proceeds with standard operation.

IV. TEST DATA & DATA TYPE

A. Test Data

Test data are acquired from the MIT-BIH Arrhythmia Database which utilises mainly Lead-II ECG recordings sampled at 360Hz with a gain of 200 V/V and an offset of 1V [11]. Recordings 100 and 101 from this database are modified with the real baseline wander signal, BWM1, acquired from the MIT-BIH Noise Stress Database to generate a realistic representation of ambulatory data. Both recordings last for 30 minutes and the algorithm is tested on the complete datasets (i.e 650k samples).

B. Data Type

Microcontroller C implementation is acquired using IEEE 754 binary floating-point format to define filter coefficients, summation points, fiducial point locations as well as the weighted piecewise linear interpolation outputs.

Filter coefficients are determined in MATLAB utilising the *fdatool*, and are expressed in transposed direct-form II structure in single precision with normalised numerator coefficients.

V. MEASURED RESULTS & DISCUSSION

A. Baseline wander estimation

The detected fiducial points and the microcontroller estimation of the baseline wander of the recording 101 with added base-

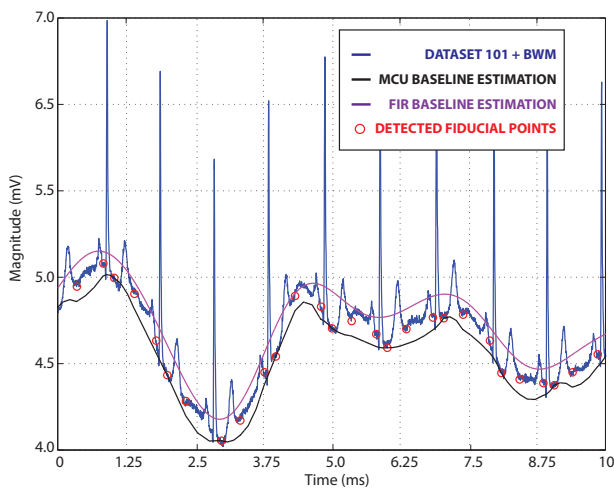
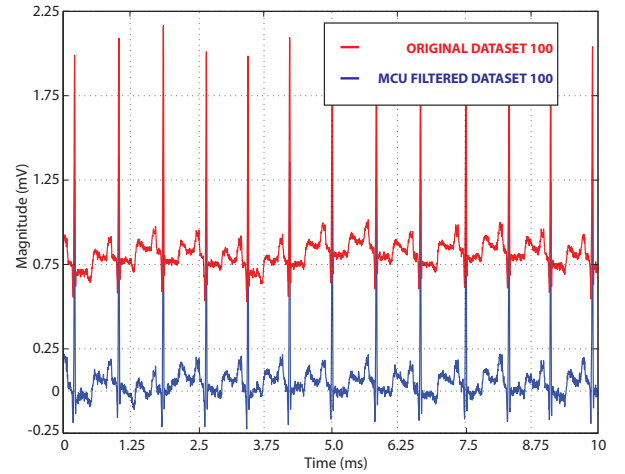


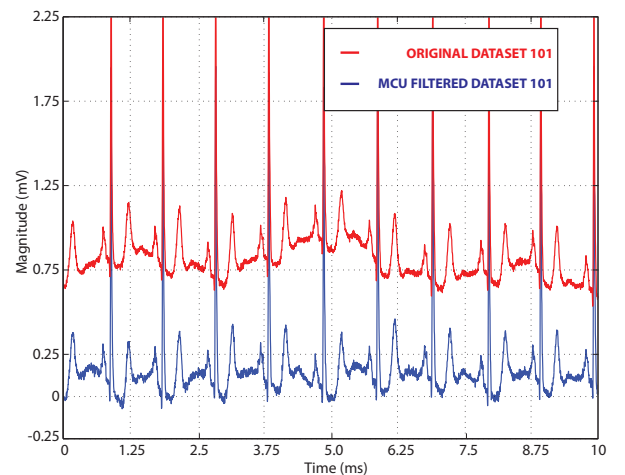
Fig. 5. MCU - based baseline wander estimation of “clean” sections of MIT-BIH Arrhythmia Database signal 101 with added baseline wander from MIT-BIH Noise Stress Database.

line wander are shown in Fig. 5. The same plot also shows the baseline drift estimation of a 12218th order equiripple low-pass FIR filter with a transition band defined from 0.57 to 0.67 Hz ($f_s=360$ Hz), a stop-band attenuation of 80 dB and a pass-band ripple of 0.01 dB. Such a filter avoids non-linear phase distortion and detects the frequency content below 0.67 Hz accurately. As can be seen, both estimations are in strong resemblance with each other.

When the complete recording 101 is processed, MSP430 baseline estimation results yield a root mean square error (RMSD) of 46.2 μ V (mean), 32.0 μ V (median) and 84.5 μ V (standard deviation) per heart beat. The high standard deviation results are due to large step changes present within the recording. When these instances are discarded, mean, median and standard deviation RMSD results per heart beat improve to 34.9 μ V, 30.9 μ V and 18.5 μ V respectively. Similarly, recording 100 RMSD results with a mean, median and standard deviation improve from 43.3 μ V, 30.5 μ V 67.2 μ V to 33.6 μ V, 29.8 μ V and 18.2 μ V respectively.



(a) MCU-based BW removal - Dataset 100.



(b) MCU - based BW removal - Dataset 101.

Fig. 6. BW removal of MIT-BIH Arrhythmia Dataset 100 and 101 with added BW from MIT-BIH Noise Stress Database.

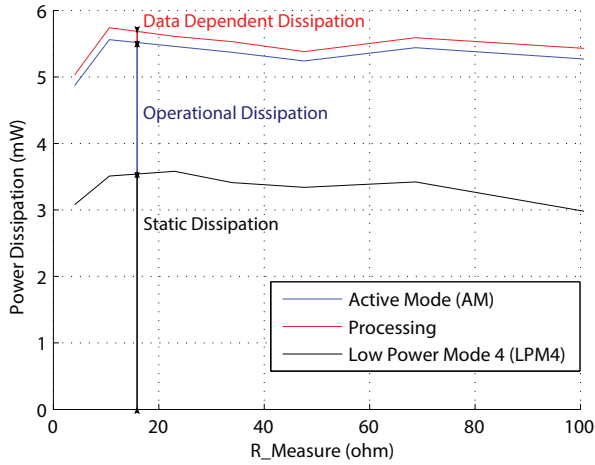


Fig. 7. Power consumption on the TI MSP430FR6989 platform.

The time domain responses of the baseline wander removal using the MSP430 microcontroller on the MIT-BIH Arrhythmia Database signals are demonstrated in Fig. 6. Both recordings, 100 and 101, depict not only the removal of the added baseline wander from the MIT-BIH Noise Stress Database, but also depict the removal of the residual baseline wander within the original dataset without distorting the ST segment.

B. Power Consumption

The power dissipation of the MSP430FR6989 launchpad is acquired through differential measurements. The registers of the microcontroller unit initially are set to low-power mode (LPM4). In this mode, the current consumption of the MCU is $2\mu\text{A}$ and all the available clocks as well as the CPU are turned off. This way, the static power dissipation of the launchpad is calculated by measuring the voltage drop on the resistors to determine the current withdrawn by the launchpad. Similarly, measurements are recorded for active mode (AM) to determine the operational and data dependent power dissipation. Fig. 7 shows the average power consumption measurements with varying resistor values. On average the total power consumption of the MSP430FR6989 launchpad is 5.6 mW, whereas the data dependent power dissipation (active mode operation + processing) is on average 2.4 mW.

The power dissipation percentages of the MSP430FR6989 launchpad are shown as a pie chart in Fig. 8. As can be seen, most of the total power consumption is statically dissipated by the launchpad (61%), whereas the remainder of the power consumption is dissipated while in active mode operation (36%) and processing (3%).

VI. CONCLUSION

In this paper, we have presented a real-time realisation of ECG baseline wander removal algorithm on an off-the-shelf embedded platform (MSP430FR6989 launchpad). Real data tests show that ST distortion during baseline wander removal is within the guidelines stated by the AHA and IEC for clinically valid ECG. In addition, the exceptionally-low computational complexity of such a system presents an opportunity for a future ultra low-power ASIC implementation.

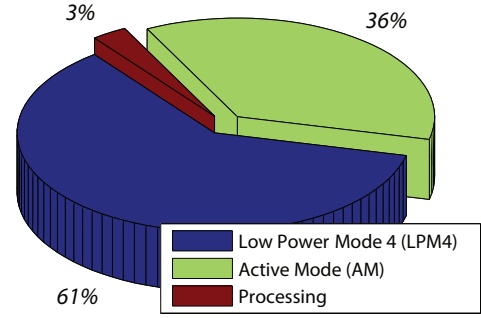


Fig. 8. Breakdown of power budget on TI MSP430FR6989 platform.

ACKNOWLEDGEMENTS

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