Multi-lead Wavelet-based ECG Delineation on a Wearable Embedded Sensor Platform

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Abstract

This work is dedicated to the sensible optimization and porting of a multi-lead (ML) wavelet-transform (WT)-based electrocardiogram (ECG) wave delineator to a state-of-the-art commercial wearable embedded sensor platform with limited processing and storage resources. The original offline algorithm was recently proposed and validated in the literature, as an extension of an earlier well-established single-lead (SL) WT-based ECG delineator. Several ML ECG delineation approaches, including SL selection according to various criteria and lead combination into a single root-mean-squared (RMS) curve, are carefully optimized for real-time operation on a state-of-the-art commercial wearable embedded sensor platform. Furthermore, these ML ECG delineation approaches are contrasted in terms of their delineation accuracy, complexity and memory usage, as well as suitability for ambulatory real-time operation. Finally, the robustness and stability of the ML ECG delineation approaches are benchmarked with respect to a validated SL implementation.

1. Introduction

A significant amount of research effort has been devoted to the automated analysis of electrocardiogram (ECG) signals, and in particular to the underlying detection of the major ECG characteristic waves, namely the QRS complex, P and T waves, so-called *ECG delineation* [1]. As a result, several automatic delineation methods working on a single ECG lead can be found in the literature [1, 2]. In practice, however, multiple leads are simultaneously acquired both in traditional clinical settings (the standard 12 leads) and in emerging ambulatory ECG monitoring (the 3-lead configuration). The deployment of delineation approaches able to exploit the multiple leads, i.e., multi-lead (ML) delineation, can potentially improve the accuracy, stability and resilience to artifacts of the characteristic waves measurements, compared to single-lead (SL) delineation [3, 4]. This is particularly relevant for the herein considered ambulatory/wearable ECG application, the quality of the measurements by the different lead may not be known a-priori (ECG electrodes installed by the patient himself) and/or may vary due various artifacts introduced during daily usage.

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The present work investigates two approaches to deploying ML delineation based a single-lead ECG delineator, namely, *lead selection* and *multi-lead combination into a single root-mean-squared (RMS) curve*. The considered single-lead delineator is based on a state-of-the-art wavelet transform-based delineator [2, 5], which exploits the time-scale description of this transform to provide a robust, efficient and reliable automated analysis of the multiresolution waves of the ECG signal. More specifically, we use a modified version of this early offline algorithm [2], which we have previously optimized for real-time implementation on a state-of-the-art commercial embedded wearable sensor platforms (EWSNs) with limited processing and storage resources *Shimmer*$^{\mathrm{TM}}$ [7]. The detailed description and validation of our optimized algorithm can be found in [6].

In addition to comparatively evaluating the delineation accuracy of the aforementioned multi-lead ECG delineation approaches, this work describes their optimization and porting to the Shimmer$^{\mathrm{TM}}$ platform. In particular, we report on the complexity and memory usage of these multi-lead approaches, and thus assess their suitability for ambulatory real-time operation.

The rest of the paper is organized as follows. In Section 2, we introduce the investigated ML delineation methods. In Section 3 we describe the applied optimization techniques to port the ML delineation methods onto an EWSN. Then, in Section 4 we present the experimental results that validate the quality of the delineation. Finally, in Section 5 we draw the main conclusions of this work.

2. Multi-lead delineation methods

Two main approaches to ML delineation methods are considered in this work. The first approach is lead selection, which simply selects among the available multiple leads the best lead, according to a given criterion, to delineate a specific or all ECG characteristic waves using the retained single-lead delineator. The second approach instead combines the multiple leads into an RMS ECG signal on which the single-lead delineator is run. In summary, the first approach tries to identify the best individual lead to extract the desired signal component(s), while the second approach seeks to provide an overall view of the entire heart in a manner that is independent of the lead system used. Both methods are further explained subsequently.

2.1. Lead selection

The automatic selection of the best lead is not straightforward in an ambulatory wearable setting. For benchmarking purposes, we consider 3 schemes: random (uniform) selection, and two different expert-based selections. The *random selection* simply selects one of the leads uniformly at random. This approach has the advantage of requiring no system configuration or training, at the expense of degraded delineation performance when the best lead is not selected (i.e., for a 2-lead system, 50% of the time). The first expert-based method (i.e., *training-based selection*) identifies the single lead providing the minimum standard deviation of the delineation error, averaged over all delineation points. This lead is then consistently selected for the delineation. This approach corresponds to a scenario, where upon system installation on the patient, the cardiologist would observe the multiple leads and select the lead allowing the best results overall. The second expert-based method (i.e., *genie selection*) represents the optimal approach, which consistently chooses, for each delineation point and for each beat, the channel with less error. It entails a two-fold increase in the complexity and memory requirements of the algorithm, as both leads have to be acquired and delineated in parallel.

2.2. RMS method

This method first combines the multiple leads into a single RMS ECG signal, on which delineation is then performed [3,4]. The RMS ECG signal $x_{RMS}[n]$ of a set of M ECG leads ($x_i[n]$ with $i = 1, \ldots, M$) is defined as:

$$x[n] = \sqrt{\frac{1}{M}\sum_{i=1}^{M} x_i^2[n]}, \tag{1}$$

where n denotes the discrete-time index. For a meaningful combination, it is crucial to remove baseline wander on each of the leads before computing the RMS [3,4]. Since the quality of the subsequent delineation depends on the baseline wander correction, the effectiveness of the following two state-of-the-art algorithms is assessed.

- **Adaptive filtering**: Baseline wander is removed using a single-tap adaptive least-mean-squares (LMS) filter, followed by a moving average filter (which helps to get a narrower transition band), as proposed in [8]. The original paper used a learning rate $\mu = 0.005$ and a moving average over 361 samples (with a sampling frequency of 360 Hz). Since the sampling rate of our system is 250 Hz, a very similar frequency response was obtained by taking $\mu = 0.007$ and a moving average over 251 samples. However, to make the system simpler to compute on an embedded platform, we instead used $\mu = 1/128 = 0.0078125$ and a moving average over 256 samples. The filter frequency response remains very similar to the original one, but it theoretically has very limited computational complexity. However, this theoretical low complexity comes at the expense of a reduced baseline wander removal capability. Moreover, its execution in a EWSN is not efficient due to the type of required operations (i.e., floating point multiplications/divisions) (cf. Section 3).
- **Morphological filtering** was proposed in [9]. It consists of two steps. The first one implements baseline correction by means of several erosion and dilation operations on the original signal. In the second step, noise is further reduced using erosion and dilation operations applied on the signal, but using special structuring elements that help retaining the peaks and valleys of the important waves, e.g., the QRS complex, the P and T waves.

3. Implementation on an Embedded Wearable Sensor Platform

In this section we present the particular EWSN used in this work and describe the optimizations applied to port the algorithm onto this platform.

3.1. The Shimmer^{TM} embedded platform

Our target WBSN is the SHIMMER^{TM} platform [7]. This platform is equipped with an ultra-low-power 16-bit microcontroller from TI (MSP430F1611 [12]) which offers a maximum frequency of 8MHz, 10KB of RAM, 48KB of Flash and some peripherals as analog-to-digital converters (ADC), a direct memory access unit (DMA) and a fast hardware multiplier. The SHIMMER also provides two radio chips (Bluetooth and 802.15.4 compliant) and an expansion port used to connect a daughter board equipped with several sensors (ECG, accelerometers, gyroscopes, etc.). The daughter board used in this work contains an application-specific integrated circuit (ASIC) that is able to read and amplify 3-lead ECGs.

Regarding the software, the applications have been programmed in C and compiled for Shimmer using the GCC-MSP v4.30 toolchain [13], which uses all the hardware resources of the target microcontroller.

3.2. Optimizations for Shimmer

To execute the proposed algorithms in Shimmer and process the ECG signal in real-time, we need to optimize their computational power and memory footprint. In all the algorithms, every sample uses 2 bytes and at least 6 buffers per lead. Then, in the case of the random and training-based algorithms, which choose one lead at the

Table 1. Results: comparison between the three lead selection methods (optimal, random, training-based) and the RMS method with the two alternative filters for baseline wander correction (adaptive and morphological).

$Method$	$Param$	P_{on}	P_{peak}	P_{end}	QRS_{on}	QRS_{end}	T_{peak}	T_{end}
2-lead [6]	Se (%)	99.87	99.87	99.91	99.97	99.97	99.97	99.97
16-bit int	P^+_{min} (%)	91.98	92.46	91.70	98.61	98.72	98.91	98.50
Optimal	$m \pm \sigma$ (ms)	8.6 ± 11.2	10.1 ± 8.9	0.9 ± 10.1	3.4 ± 7.0	3.5 ± 8.3	3.7 ± 13.0	-2.4 ± 16.9
2-lead	Se (%)	98.41	98.30	98.17	99.74	99.74	99.44	99.37
16-bit int	P^+_{min} (%)	92.30	92.65	92.44	99.29	99.33	99.33	98.97
Random lead	$m \pm \sigma$ (ms)	11.2 ± 17.1	10.6 ± 14.5	-4.1 ± 15.6	7.0 ± 10.2	5.3 ± 11.3	4.8 ± 20.8	-4.9 ± 25.0
2-lead	Se (%)	98.64	98.64	98.64	99.97	99.97	99.73	99.73
16-bit int	P^+_{min} (%)	92.75	93.43	92.91	99.58	99.58	99.57	99.36
Training-based	$m \pm \sigma$ (ms)	14.8 ± 12.9	15.4 ± 9.5	1.3 ± 11.1	8.6 ± 7.7	3.1 ± 9.5	5.2 ± 14.1	-3.1 ± 19.3
RMS	Se (%)	95.88	95.88	95.88	99.60	99.63	97.57	97.54
16-bit int	P^+_{min} (%)	94.33	94.27	94.09	98.96	98.96	99.03	98.88
Adaptive filtering	$m \pm s$ (ms)	8.3 ± 23.1	13.9 ± 18.3	-2.9 ± 19.8	5.6 ± 10.1	7.8 ± 11.3	8.7 ± 22.6	-7.1 ± 28.5
RMS	Se (%)	98.28	98.28	98.31	99.78	99.78	99.66	99.55
16-bit int	P^+_{min} (%)	92.87	92.87	93.09	99.18	99.15	99.19	98.93
Morph. filtering	$m \pm s$ (ms)	1.5 ± 14.2	15.0 ± 10.8	-0.3 ± 13.2	8.6 ± 7.8	9.4 ± 9.3	5.9 ± 19.5	-10.7 ± 24.5
Tolerances		10.2	–	12.7	6.5	11.6	–	30.6

beginning of the execution, we store in each buffer 512 samples of the input signal and of its WT-transform (on each of the five scales at a certain instance of time), which requires 6.8KB of memory (6KB for the buffers and 0.8KB for auxiliary variables). Thus, they fits in the 10KB memory in the MSP430 microcontroller. Then, for the optimal ML delineation algorithm, since it needs 12 buffers because two leads are used for delineation, we have adjusted its buffer's length to 256 samples and its total memory utilization is 6.8KB. Last, in the case of the RMS algorithms, they require ten buffers: 2 for the input signals (1 per lead), 2 for the filtered signal (1 per lead), 1 for the RMS curve, and five for the different scales of the WT-transform. Also, both algorithms need 0.5KB for auxiliary variables. Hence, we have adjusted their buffers' length to 256 samples, and their final memory footprint is approximately 5.5KB, fitting in the 10KB limit of the MSP430.

Regarding computational complexity, the lead selection algorithms require 5% of the time to perform on-line processing per lead, which is the case of the random and training-based algorithms, while the remaining 95% the MSP430 microcontroller is in sleep mode. Then, the optimal ML delineation algorithm uses the microcontroller 10% of the time, as it uses two leads, which still enables a large amount of time in sleep mode. On the contrary, the RMS algorithms are more computationally intensive due to their initial filtering phase of the two input signals (one per lead) and when the RMS curve is calculated. Thus, apart from the 5% of the time in the delineation process, they both use 2.5% of the time in the RMS calculation requires, and then the largest amount of time in the filtering process: 56% in the case of the adaptive filter and 23% in the case of the morphological filtering. In fact, even though the the adaptive filter requires only very few operations (4 additions/substractions, 4 multiplications and 1 division) per sample and simple moving average, they are all floating point operations, which are very expensive (from the performance viewpoint) to execute in small microcontroller, since it does not have any hardware support for floating point operations and they are replaced by software emulation code. Thus, this results clearly show the need for adapting the original algorithm and underlying operations to the specific type of EWSN and included microcontroller.

4. Validation and Experimental Results

For the validation of this work, we run all the experiments using as input the 105 records of the QT database (QTDB) [10]. The QTDB is a free-access database which consists of 15-minute excerpts of two-channel ECG recordings. This database was created for the evaluation of ECG delineation algorithms. For this purpose, the input ECG records have been manually annotated by expert cardiologists. The performance of the algorithms is measured comparing the results obtained by our proposed automated algorithm with respect to the manual annotations.

To compare the results obtained by our algorithms with the ones contained in QTDB, we use four metrics: sensitivity, positive predictivity, mean error and standard deviation. The sensitivity and positive predictivity are defined as $Se = TP/(TP + FN)$ and $P^+ = TP/(TP + FP)$, respectively, where TP is the number of true positive detections, FN the number of false negative detections and FP the number of false positive detections. The mean error (m), which is computed as the average of the errors across all the records, shows how close the results of the algorithm are to those that have been manually annotated in the database, while the standard deviation of the error (σ), which is defined as the average of the standard deviation of each record, gives us information about the stability of the detections.

4.1. Delineation results

The validation results on the QTDB obtained for the various ML delineation methods discussed in this paper are compiled in Table 1. In addition, the last row indicates the two-standard-deviation tolerances set by the Common Standards for Electrocardiography (CSE) committee [11].

Comparing the three lead-selection approaches, it is confirmed that the optimal approach, which consistently chooses the best lead for each wave, naturally exhibits the best delineation accuracy for all fiducial points. The training-based lead selection approach, which chooses the lead with minimum standard deviation for all the points, shows a slightly worse performance, while the random selection comes last. As an illustration, the differences (mean$\pm$standard deviation in ms) between automatic real-time delineation on the embedded platform and the expert annotations for the faint P wave were as follows: training-based lead selection achieved 14.8$\pm$12.9, slightly worse than the genie lead selection approach (8.6$\pm$11.2) and 1 sample better than the random lead selection (11.2$\pm$17.1). It is worth mentioning that since the results of random selection vary from one execution to another, the average of 15 executions is computed in order to minimize the effect of the random selection in the results.

Regarding the RMS-based ML delineation, it is relevant to note that the results reported in Table 1 were obtained after several modifications/optimizations on the single-lead WT-based delineator used as a second stage of the previous lead selection delineators [6]. These modifications were introduced to take into account the specific characteristics of the RMS ECG signal, and are as follows: (1) The QRS detection threshold ϵ_2 was divided by 2 compared to its original value; (2) For P and T waves, only maxima followed by minima on scales 2^4 and 2^5 were considered, due to the special shape of the RMS ECG; (3) The coefficient to compute $\xi_{P_{on}}$ was reduced from 0.5 to 0.25.

The results of RMS-based delineation with adaptive filtering pre-processing are reported in Table 1. They show that QRS and T delineation are within acceptable range (i.e., close to the tolerances), while the P wave is poorly delineated. This is due to the fact that this faint wave is the most affected by the bad quality of the baseline wander removal of the simple filter used here. This is further confirmed by the significantly better delineation accuracy when the more effective morphological filter is used in the pre-processing stage of RMS-based delineation. As shown in Table 1, this last approach to RMS-based ML delineation outperforms random lead selection, and falls slightly short of equaling the training-based lead selection. In particular, it was found to achieve 1.5$\pm$14.2, without requiring expert training for lead selection, yet critically depending on successful baseline wander correction of the multiple lead prior to combination. It remains to be confirmed that an even better baseline wander removal strategy, such as cubic spline interpolation, establishes the RMS-based ML delineation as the most accurate, stable and robust approach to ML delineation.

5. Conclusions

This work has investigated several ML techniques, as a means to improve the accuracy of ECG signal delineation. These techniques have been ported and validated in real-time on a commercial wearable sensor platform. Our results suggest that a training-based lead selection provides good results, without any added complexity to the core WT- based delineation algorithm. However, this technique is probably not appropriate for ambulatory settings, where expert intervention may not be available and electrode placement may change due to body movements. As far as RMS-based ECG delineation is concerned, our results indicate that the quality of the results highly depends on the effectiveness of the mandatory baseline removal pre-processing stage. When a good baseline wander removal technique is used, the delineation results are very close to the ones obtained by the expert-based lead selection methods, while obviating the need for expert intervention.

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