REAL TIME ELECTROCARDIOGRAM SEGMENTATION FOR FINGER BASED ECG BIOMETRICS

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Abstract: In biometric recognition based on Electrocardiographic (ECG) signals, there are two main approaches for feature extraction: fiducial and non-fiducial. Fiducial methods use points of interest within single heartbeat waveforms, obtained by segmenting the ECG signal using QRS complexes as a reference. In this paper we study several QRS detection algorithms, with the purpose of determining what is the best algorithm in the context of finger based ECG biometrics using fiducial approaches; our main focus is the real-time segmentation of ECG signals resulting on a set of single heart beats. We propose a method combining the adaptive characteristics of the algorithm by Christov, with the strategy of the widely adopted Engelse and Zeelenberg algorithm. Experimental results obtained for real-world data show that online approaches are competitive with offline versions, and represent a contribution for the realization of real-time biometric recognition.

1 INTRODUCTION

Electrocardiographic (ECG) signals are a recent trend in biometric recognition; they exhibit very appealing characteristics, such as intrinsic liveliness detection, and the fact that they do not depend on external physical landmarks, therefore being difficult to spoof.

There are two main approaches for ECG feature extraction: fiducial and non-fiducial. Fiducial methods use points of interest within single heartbeat waveforms (Biel et al., 1999; Shen et al., 2002; Israel et al., 2005; Silva et al., 2007; Lourenço et al., 2011), while non-fiducial aim at extracting discriminative information without localizing reference points (Chan et al., 2008; Coutinho et al., 2010).

Fiducial approaches locate reference points based on the detection of single heartbeat waveforms. These are obtained by segmenting the ECG signal, and QRS complexes are generally used as a reference due to their singularity. Figure 1 shows the typical ECG signal, with QRS complexes identified. This complex represents the depolarization and re-polarization phenomenon of the ventricles.

As with other biometric traits, current research focuses on the usability and the design of more convenient acquisition setups, that can be used for practical and daily applications. The acceptance of ECG based methods requires real-time or near real-time authentication/identification, which can be obtained diminishing the acquisition and processing time.

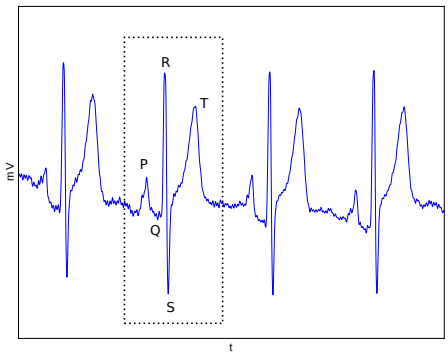

Figure 1: ECG acquired at the chest from one patient of the PTB-BIH (Oeff et al.,) control subjects database. The ECG waveform is labeled with the corresponding complexes. The P wave corresponds to the sinoatrial node triggering impulse, the QRS complex is associated with the depolarization process, and finally the T wave reflects the repolarization process.

In this paper we review several QRS detection algorithms, with the purpose of determining what is the best algorithm for finger based ECG biometrics using

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fiducial approaches, focusing on real-time identification of single heart beats.

The remainder of the paper is organized as follows. In Section 2, an overview of QRS detection algorithms is presented. In Sections 3 and 4 we provide a brief overview of representative algorithms of offline and online QRS detection algorithms, and describe the proposed modifications for both offline and online algorithms. Finally, in Sections 5, 6 and 7 we outline the experimental setup, the main results and conclusions, respectively.

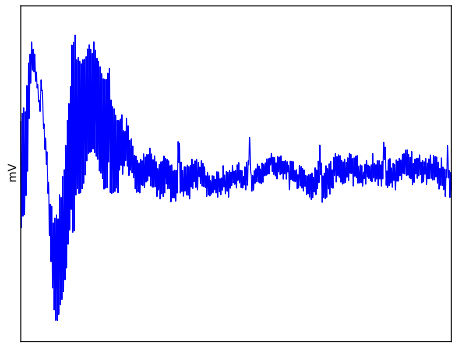
2 RELATED WORK: QRS DETECTION ALGORITHMS

The automation of electrocardiogram analysis processes found in the Holter test and in real-time patient monitoring, led to the development of algorithms for the detection of QRS complexes. Due to its morphology (see Figure 1), it serves as basis for computing the heart rate, as a reference point for cardiac cycle classification schemes, and ECG data compression algorithms (Kohler et al., 2002). There are approaches based on signal derivatives and digital filtering (Friesen et al., 1990), or more complex approaches based on artificial neural networks, genetic algorithms, wavelet transform (for more details see (Kohler et al., 2002)).

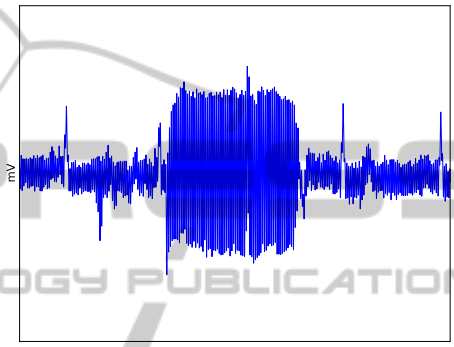
Using the ECG as biometric, the work in (Lourenço et al., 2011) proposes the acquisition of this signal at finger level, through a minimally intrusive 1-lead ECG setup recurring to Ag/AgCl electrodes without gel as interface with the skin. This type of setup implies more noise than the traditional acquisition at the chest, in particular when using multiple leads. Figure 2 illustrates signals collected at the fingers using dry Ag/AgCl electrodes, showing common artifacts. Figure 2(a) corresponds to the presence of motion artifacts; in this case the amplitude of the ECG signal is quite close to the noise amplitude; Figure 2(b) illustrates a case where signals are corrupted by high frequency powerline noise and electromyogram noise.

The need for robust algorithms is clear when we compare the above mentioned signals, with traditional ECG signals collected at the chest using conductive gel, as depicted in Figure 1, where the noise is practically inexistent.

The development of algorithms for real time analysis of the ECG begun in the 80's. In (Pan and Tompkins, 1985), an online QRS detection algorithm was implemented in assembly language. It consisted in digital bandpass filtering to remove the noise, differentiation to obtain information about the slope of the QRS, followed by squaring to intensify this slope and finally a moving window integrator to produce a signal that included information about the slope and the width of the QRS complex. This process is divided in three phases: learning phase 1; learning phase 2; detection. The learning phase 1 required 2s to initialize the detection thresholds. The learning phase 2 requires two heartbeats to initialize the RR-interval average and RR-interval limit values. The detection phase produces pulses for each QRS complex. The thresholds and other parameters of the algorithm are periodically adjusted, to adapt to changing characteristics of the signal.



(a) Motion artifact



(b) Electrical and electromyogram interference

Figure 2: Example of finger ECG readings from two different subjects, collected using dry Ag/AgCl electrodes. As we can observe, the signal quality is significantly worst than the one obtained at the chest (see figure 1.).

In (Christov, 2004), an algorithm is presented that follows the same principles, proposing the detection based on an adaptative threshold. over the so called complex lead signal, $y[n]$. This signal is obtained by averaging the absolute value of the differentiated versions of all available leads. The process is initiated by digitally filtering the input signal, $x[n]$, to remove power-line interference and electromyographic noise. The detection is performed by verifying when $y[n]$ is higher than a threshold, obtained through the

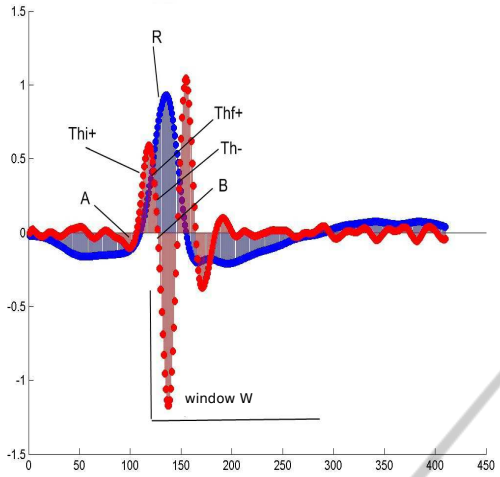


Figure 3: Adaptation of the Engelse and Zeelenberg algorithm for QRS detection algorithms (Engelse and Zeelenberg, 1979). In blue the original signal, $x[n]$, and in red $y_2[n]$.

linear combination of three components: M (Steep-slope threshold); F (Integrating threshold for high frequency signal components); R (Beat expectation threshold).

Before presenting our QRS-complex detection in real time, we overview the state of the art in offline QRS detection, since in previous works on ECG biometric recognition, this type of algorithms was used.

3 OFFLINE QRS DETECTION AND IMPROVEMENTS

In (Friesen et al., 1990), nine different offline QRS detection algorithms are compared in the presence of noise. We build on the work by (Engelse and Zeelenberg, 1979), since it is considered to be one of the more robust.

The QRS detection method by Engelse and Zeelenberg consists of the following. A digitally filtered version of the ECG signal, $x[n]$, is passed through a differentiator (Eq. 1), and then by the low pass filter (Eq.2):

$$y_1[n] = x[n] - x[n-4], \quad (1)$$

$$y_2[n] = \sum_{i=0}^{4} c_i . y_1[n-i], \text{ where } c_i = [1,4,6,4,1] \quad (2)$$

Figure 3 presents the input signal, $x[n]$, and the corresponding processed signal $y_2[n]$. The R peak detection is based on the analysis of the negative lobs of

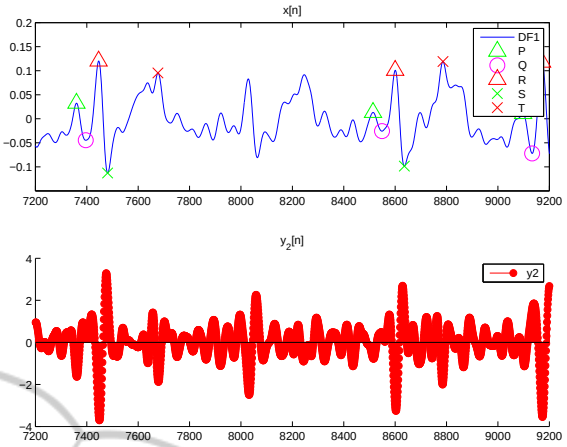


Figure 4: Missing R detection.

$y_2[n]$, and it is identified automatically, by scanning $y_2[n]$ using two thresholding operations.

The detection begins by finding the interval $n \in \{n_{thi+}, n_{thf+}\}$, indicated in Figure 3, whose amplitudes verify the condition: $y_2[n] > Th$, with $Th = 0.6\max(y_2[n])$. Then, we look for a $160ms$ long window, W, to the right of n_{thf+}, where the condition $y_2[n] < -Th$ holds for a specified number of consecutive points (experimentally we found this number to be at least 10 points). In (Engelse and Zeelenberg, 1979) more thresholding operations are proposed, but we considered the described conditions enough.

Upon finding a candidate R peak, the original signal, $x[n]$ is scanned inside the obtained windows, W, and the peak is determined as the time instant correspondig to the highest amplitude signal.

Taking as reference the identified R peak, we continue the analysis of $y_2[n]$ within its left and right neighborhoods, determining the time instants were it starts to be positive and comes down to negative again. Within these intervals, we take the minimum values of $x[n]$ as the beginning of the Q and S complexes, respectively.Using as reference the starting of the Q and S complexes, we analyze $x[n]$ finding the maximum on their neighborhood to find the complex Q and S.

This algorithm presents the problem of having fixed thresholds, and if the analyzed ECG signal has amplitude variations, its robustness is affected. As an example, let's consider the case presented in Figure 4, where one of the single heartbeat waveforms is not recognized. As we can see by analyzing $y_2[n]$ (in red), the negative lob is much less pronounced than in the case of the complexes on the left and right, correctly identified.

In order to solve this situation we tried to lower the threshold Th, but doing so, the number of false

positives increases. To compensate for this phenomena we introduce a second threshold, which enables the identification of negative lobes comprising R-peak time instants. Its value is obtained from the lowest value of $y_2[n]$ found in the analysis, and the condition defined as:

$$\begin{aligned} &y_2[n] < ThNew \\ &ThNew = 0.7\min(y_2[n]) \end{aligned} \quad (3)$$

4 PROPOSAL FOR ONLINE QRS DETECTION

Motivated by the offline algorithm of Engelse and Zeelenberg, where the R complex is identified thresholding two lobes of a differentiated version of $x[n]$, we propose to combine that strategy with adaptative thresholds estimated along the acquisition process.

To determine this adaptive threshold we build on the work by (Christov, 2004), using a threshold estimation scheme similar to the one in (Christov and T, 2002) for the threshold M. In that work, the threshold M is calculated using a temporal sliding window of 5s. They form a buffer $MM = M_1, M_2, M_3, M_4, M_5$, consisting in the concatenation of 5 partial thresholds, M_i, calculated by Equation 4 in each 5s sliding window; M is obtained according to Eq. 5.

$$M_i = 0.6\max(y[n]), \quad (4)$$

$$M = \begin{cases} M_i & \text{during the initial } 5s \\ \frac{1}{5}\sum_{i=1}^{5} M_i & \text{rest of acquisition} \end{cases} \quad (5)$$

The process continuously updates the partial thresholds, erasing the older threshold, left shifting the intermediate thresholds and calculating a new M_5. This new partial threshold, M_5^{new}, can become quite high, due to premature ventricular contraction, so if $M_5^{new} > 1.5M_5$, then $M_5^{new} = 1.1M_5$.

The algorithm doesn't allow detections of QRS peaks 200 *ms* after the last one, and the M threshold is decreased during the interval 200 to 1200ms following the last detection, at a low slope, until reaching 60% of its value at 1200ms. After 1200ms, M remains unchanged until a new detection is obtained.

Notice that the R peak detection algorithm by Engelse and Zeelenberg can be performed in real-time, since the computations of equations 1 and 2 only requires a buffer of 4 samples. Moreover the scanning of $y_2[n]$ can be performed based on a sliding window, following the approach of Christov.

With this approach we expect to obtain better decision rules for the detection of R peaks.

5 EXPERIMENTAL SETUP

To evaluate and compare the described algorithms, we performed extensive acquisitions, collecting data from 62 subjects (47 males and 15 females) with an average age of 31.1±9.46 years. Subjects were only asked to rest their left/right hands in a setup built for this propose.

Two custom ECG sensors (Silva et al., 2011) were used for signal acquisition, one connected to the Ag/AgCl electrodes, and another connected to Electrolycra strips placed at the index and middle finger levels, as depicted in Figure 5. The ECG sensors add a total gain of 1000 and analog band pass filtering between the 1-30Hz range.

Figure 5: Experimental apparatus.

To avoid ground coupling between both sensors, two independent biosignal acquisition units were used, one per sensor. Data acquisition was performed using the commercially available bioPLUX research system (PLUX,), which enables Bluetooth wireless transmission of the collected signals to the base station. We used a sampling frequency of 1000Hz, and 12−bit resolution.

Synchronization of the acquisition units was performed optically using a syncPLUX kit and a light-dependent resistor (LDR) (PLUX,). To one of the systems a triggering switch was connected, which simultaneously activated the digital input port of the system and a LED. To the other system, a LDR was connected to one of the analog input channels, and placed in direct contact the LED of the first system, in such way that a synchronization signal was obtained whenever the LED was lit.

This allowed us to have the data collected by each system synchronized, without recurring to any electri-

cal connection between them. Signals were acquired during a period of approximately 2 minutes, in which the supervisor in charge of the experimental procedure would describe the experiment, goals and related work.

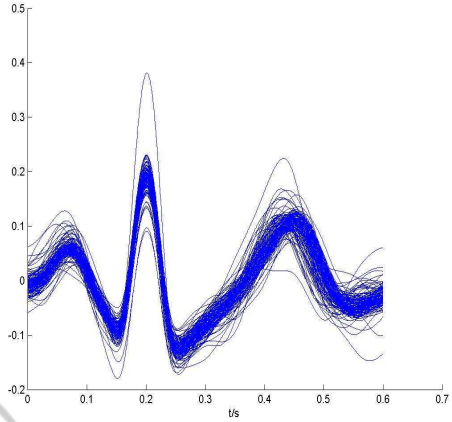
6 RESULTS AND DISCUSSION

Table 1 summarizes the results of the several approaches, both for the signal acquired using the Ag/AgCl electrodes and Electrolycras. The offline algorithms of Engelse and Zeelenberg are denoted by *EG-Butter* and *EG-FIR*; the improvement obtained using a third threshold by *EG-3*; and for the online algorithms, the Christov algorithm is denoted by *Chr*, and the proposed combination by *Chr+EG*.

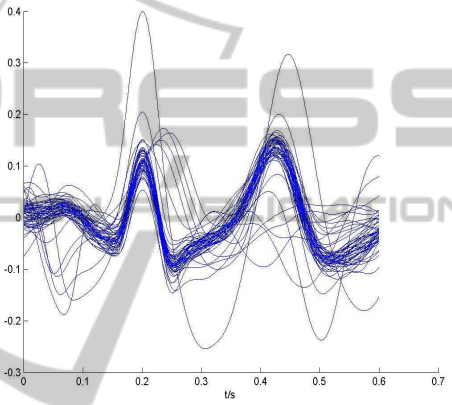
To quantify the performance of each algorithm, we present the number of segmented waves, and the mean and standard deviation of the percentage of the ones considered valid, taking as population the full data set. A segment is considered valid if the obtained RR interval does not deviate from the mean RR interval in more than 10%. The rational of this criterion is that a deviation above this margin should be due to segmentation errors, since acquisitions at rest and during a short period of time have very stable RR intervals.

The number of segmented heartbeat waveforms obtained from the dry Ag/AgCl electrode signals is higher than the ones obtained by the Electrolycra, revealing that the later signals have more noise. Comparing the performance of the online vs offline algorithms, as expressed in the table, one can observe that offline algorithms obtain more segments than online versions, but the percentages of valid segments are similar.

The algorithm that exhibits better performance is the Engelse and Zeelenberg, both using Butterworth filters - *EG-Butter*, or using Fir filters - *EG-FIR*. Regarding the online algorithms, the original algorithm of Christov - *Chr*, is the one that presents higher number of segments. Our approach that combines the adaptative threshold with the Engelse and Zeelenberg is slighty worst. Figure 6 presents an example these segmentations,with the single heartbeats superimposed and aligned according to the *R* peak. One can see than even highly noisy single heartbeats are being correctly segmented.



(a) Segmentation 1



(b) Segmentation 2

Figure 6: Example of segmentation of finger ECG readings from two different subjects.

7 CONCLUSIONS

In this work we studied the segmentation of ECG signals acquired at the fingers using QRS-complex detection algorithms. This type of process is of paramount importance in the fiducial based algorithms, since they require reference points to be correctly located on single hearbeat waveforms.

We focused an algorithm for offline ECG segmentation by adaptation of the Engelse and Zeelenberg algorithm, and the Christov algorithm for online ECG segmentation. The online approaches have shown to be competitive with offline versions, but their performance is slightly worst. On the ECG biometric point of view, these algorithms represent a contribution for performing real-time biometric recognition.

As future work we intent to use a benchmark annotated ECG dataset to corroborate these conclusions.

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Table 1: Experimental results for ECG Segmentation.

Type of Electrodes	Type of Processing	Algorithm	#segments	%valid - mean	%valid - std
Ag/AgCl	Offline	EG-Butter	7614	96.5	6.6
		EG-FIR	7322	97.9	4.3
		EG-Butter-3	7625	96.4	6.7
		EG-FIR-3	7719	97.8	4.6
	Online	Chr	6482	94.5	12.5
		Chr+EG	5971	92.4	10.4
Electrolycra	Offline	EG-Butter	6692	94.0	11.4
		EG-FIR	6244	93.4	11.6
		EG-Butter-3	6712	93.9	11.4
		EG-FIR-3	6545	94.2	10.5
	Online	Chr	5550	90.8	15.7
		Chr+EG	5044	84.5	18.5

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