On Real Time ECG Segmentation Algorithms for Biometric Applications

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Abstract: Recognizing an individual's identity through the use of characteristics intrinsic to that subject is a biometric recognition problem with increasingly number of modalities and applications. Recently, the electrical activity of the heart (the Electrocardiogram or ECG) has been explored as an additional modality to recognize individuals. The ECG signal contains several features, which are unique to each individual. The preprocessing of the ECG signal and the feature extraction steps are crucial for biometric recognition to be successful. In fiducial approaches, this last step is accomplished by correctly detecting the heart beats, and performing their segmentation to extract the biometric templates afterwards. In this work, we present an overview of the different steps of an ECG biometric system, focusing on the evaluation and comparison of multiple real-time heart beat detection and ECG segmentation algorithms, and their application to biometric systems. An evaluation and comparison of the algorithms with annotated datasets (MITDB, NSTDB) is presented, and methods to combine them in order to improve performance are discussed.

1 INTRODUCTION

Biometric recognition, or biometrics, is a growing research field in which the purpose is to automatically recognize a subject using his intrinsic characteristics (Jain et al., 2004; Jain et al., 2007), such as: physiological (e.g., Electrocardiogram), anatomical (e.g., fingerprint, iris) or behavioral (e.g., keystroke, signature). The latest trends in the field point towards the multibiometrics approaches, which use one or more of these inputs and they work by performing a pattern recognition scheme, and assessing whether the user being tested is genuine or not, i.e., the system is able to recognize the user, or imposter (a user that is not who he/she claims to be or is not registered in the system's database). Three concepts stand out in any biometric application: i) enrollment: the initial registration process, so that the system has information to use later for identity recognition; ii) authentication: the recognition process in which the subject first provides a claimed identity, the biometric templates are acquired and compared to the templates of the claimed user, and a decision is made (genuine/imposter); iii) identification: the recognition process in which the subject does not provide any prior information about his/her identity, hence the biometric system has to compare the acquired templates with all the templates stored in the database.

Multiple scenarios and applications can benefit from biometrics, such as granting/denying access to secure areas or resources (e.g., a computer), remote identity verification, and personalization of assets (e.g., intelligent houses and cars), among many others (Jain et al., 2011).

Our work is focused on Electrocardiogram (ECG) based biometrics (Biel et al., 2001; Wang et al., 2008; Shen, 2005; Israel et al., 2005; Lourenço et al., 2011), a recent trend in this field. The ECG of each individual has been shown to possess unique features among individuals (Israel et al., 2005); furthermore, the ECG holds several other biometric-relevant properties, such as: (a) it is hard to synthesize; (b) it is continuously available; (c) it may be acquired non-intrusively; and (d) it has a straightforward liveliness detection.

In developing a real-time ECG based biometric system, different challenges emerge, such as: (i) data acquisition; (ii) signal processing; (iii) information extraction; and (iv) biometric pattern recognition. The first step deals with obtaining the raw ECG data through a reliable, repeatable and non-intrusive procedure. This raw data may contain noise and other artifacts, and as such, signal processing techniques are needed to enhance the signal quality. The next step is to extract relevant subject-dependent information and feed it to the biometric system so that recognition can

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be performed.

There are two types ECG based biometrics methods: fiducial (Biel et al., 2001; Wang et al., 2008; Shen, 2005; Israel et al., 2005) and non-fiducial (Coutinho et al., 2010; Chan et al., 2008). In the fiducial case, the crucial step in extracting information from the ECG is to correctly detect each of the heart beats. The non-fiducial methods extract information without the help of reference points.

We focus on the fiducial case and therefore, the heart beat detection and ECG segmentation algorithm is of utmost importance.

One of the major research lines in ECG biometrics has been focusing on the development of non-intrusive measurement methods (Silva et al., 2011b), leading to increased measurement noise. Furthermore, so far, researchers have focused on offline processing, which limits the deployment and applicability of currently available ECG-biometrics techniques in a real-world scenario. In this paper, we present an overview and comparison of multiple real-time segmentation algorithms, taking into account the influence of measurement noise on the biometric performance. To improve robustness and performance, we propose and evaluate a set of different voting methods to combine the output information of the segmentation algorithms.

The rest of the paper is organized as follows: Section 2 provides background information about the ECG and it's application to biometric recognition; Section 3 deals with the ECG based biometrics steps; Section 4 presents the experimental protocol and discusses the results obtained; and Section 5 concludes the paper and gives some future work ideas.

2 BACKGROUND

The heart has a set of specialized cells with self-excitatory properties, which produce the electrical impulses that trigger the mechanical action of the cardiac muscle fibers; the Electrocardiogram (ECG) is the measurement of its electrical activity over time. Typically, the ECG is acquired with a set of electrodes on the thorax. Placing electrodes on the thorax is not practical in a biometric point-of-view, and recently other approaches have been presented, such as the one in (Lourenço et al., 2011; Silva et al., 2011b), in which a 1-lead setup for ECG signal acquisition at the fingers using Ag/AgCl electrodes without gel is proposed.

For a healthy human heart, the ECG waveform for each heart beat resembles the one depicted in Fig. 1: it is composed of the P, Q, R, S, and T waves and beat detection is usually performed by searching for each R-peak or QRS complex.

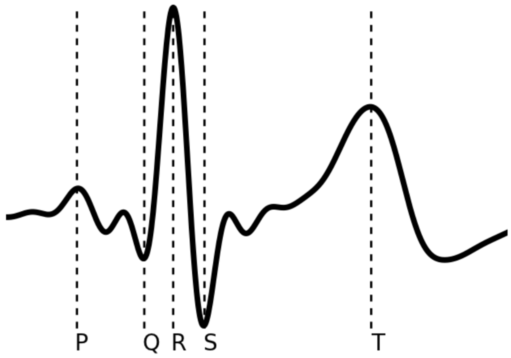


Figure 1: ECG heart beat example. The corresponding ECG signal was acquired at the fingers using the setup proposed in (Silva et al., 2011a).

Before being able to extract any information, the ECG signal needs preprocessing due to measurement noise and other artifacts which may be contaminating the signal (e.g., motion artifacts). This step is performed by applying a specific filter, designed to enhance the signal quality, while avoiding distortion and loss of relevant information.

3 ECG BASED BIOMETRICS

The architecture of an ECG biometric system follows the block diagram of Fig. 2: the raw ECG is acquired, preprocessed and converted to a digital format; digital signal filtering techniques are applied and QRS detection is performed. With the QRS complexes detected, the ECG signal is divided in segments corresponding to individual heart beats. Different features may be extracted from the heart beat waveform, such as: QRS complex duration, P, Q, R, S, and T waves amplitudes and onsets, (Biel et al., 2001; Chung, 2000). Features are then used as input to the biometric system, where pattern recognition is performed. In our case, the patterns correspond to ECG signal windows of 600ms around the QRS complexes: 200ms to the left and 400ms to the right of the R peak. These values were selected according to the typical physiological duration of the P-Q and S-T complexes.

3.1 Preprocessing

To enhance the ECG signal quality and increase the signal-to-noise ratio, we designed a 300 order band pass Finite Impulse Response (FIR) filter with a Hamming window, and cutoff frequencies of 5Hz to 20Hz. These specifications, take into account the ECG infor-

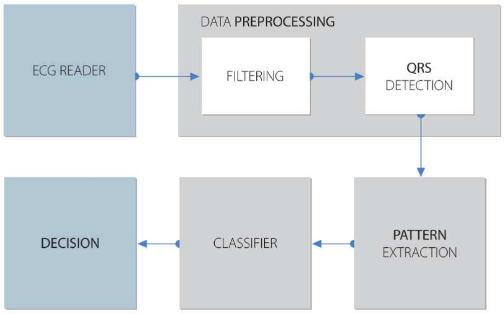


Figure 2: Block diagram of an ECG based biometric system.

mation bandwidth, and empirical considerations extracted from the heuristic analysis of the signal. Concerning real time applications, the signal is acquired and filtered in frames, and thus a method to process each frame and merge them into a meaningful signal is required. One way to solve this problem is to use the overlap-add method (Oppenheim and Schafer, 1975). Fig. 3(a) shows an example of a raw ECG signal acquired at the fingers using the protocol proposed in (Silva et al., 2011a) and Fig. 3(b) is the corresponding filtered signal with the overlap-add FIR method.

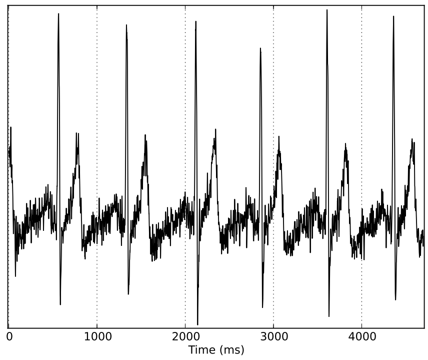
3.2 QRS Detection

We evaluated five QRS detection-ECG segmentation algorithms: I. Christov (CHRIS) (Christov, 2004), Engelse and Zeelenberg (EZEE) (Engelse and Zeelenberg, 1979), P. Hamilton (HAM) (Hamilton, 2002), H. Gamboa (GAMBOA) (Gamboa, 2008), and ECG Slope Sum Function (ESSF) (Zong et al., 2003).

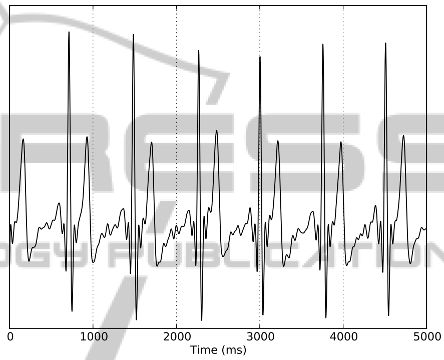
I. Christov proposes a QRS complex detection algorithm which applies an adaptive threshold to a constructed complex lead signal. This threshold is a linear combination of the following components: a steep-slope threshold (M); an integrating threshold (F); and a beat expectation threshold (R), (Christov, 2004).

The algorithm by Engelse and Zeelenberg was proposed in 1979. In this work, we used the modified real time version of this algorithm proposed in (Loureno et al., 2012) (EZEEMod). It applies a differentiator, a low pass filter and scans the resulting signal, in a 160ms moving window, with adaptive thresholds. These are updated each time and are a function of the maximum signal amplitude. Furthermore, the algorithm ignores peaks within a 200ms interval of the previous detected R-peak.

Hamilton proposed a QRS complex detection algorithm that works by first preprocessing the ECG signal and then scanning and evaluating it according to a set of rules related to the interval between consecutive R peaks, (Hamilton, 2002).



(a) Raw ECG Signal.



(b) Overlap-add FIR filtered ECG Signal.

Figure 3: Raw and filtered versions of an ECG signal acquired at the fingers using a sampling frequency of 1000Hz and a frame size of 100ms.

For QRS detection, H. Gamboa proposes in (Gamboa, 2008) an algorithm that involves signal normalization via histogram computation and threshold setting and R peak detection via ECG signal derivative and threshold surpassing.

The Slope Sum Function (SSF) is a weighted moving average function which enhances the upslope of the ECG signal and thereby makes the R-peak detection easier. It was applied to the Blood Volume Pulse (BVP) signal in (Zong et al., 2003). In this work, we adapted the SSF for the ECG signal.

3.2.1 QRS Complex Validation through Voting

We have also implemented a QRS detection algorithm that combines and validates the information from the above five algorithms. In summary, we ran each algorithm separately and then decide if each detected QRS complex is valid by voting. Two criteria were used: a) one of the algorithms is taken as reference and each QRS complex is considered valid only if at least two of the other algorithms also detected the same QRS complex (within a 50ms tolerance) - *majority* voting;

and b) from the set of all QRS complexes detected (by the five algorithms), we validate only those that are common to all five algorithms - *unanimity* voting.

3.3 Segmentation

After the ECG preprocessing, we perform ECG segmentation by evaluating each QRS complex and clipping the ECG signal in an interval 200ms to the left of the R-peak to 400ms to the right (values based on the typical duration of the P-Q and S-T complexes). In this way, information from the QRS complex as well as from the P and T waves is assured, and an ECG pattern is generated for each heartbeat. Fig. 4 illustrates the procedure.

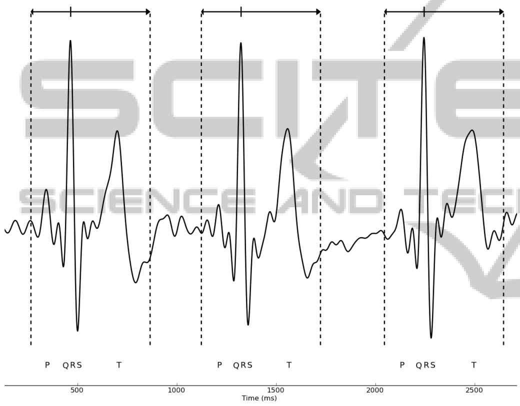


Figure 4: ECG segmentation example: the arrows and dashed lines indicate the length and limits of each segment.

On a side note, compression may occur in the ECG signal when the heart rate increases significantly and the fixed -200ms to +400ms interval would not be the most suited one as it may contain information of 2 heart beats. This was not a problem in our experimental protocol but future work should take this in consideration.

3.4 Pattern Recognition

In this work, pattern recognition is performed by evaluating the Euclidean Distance (ED) between different ECG patterns. In the enrollment phase, the subject interacts with the biometric system, ECG data is acquired, filtered, segmented and the ECG segments (or combinations of them) are saved as ECG patterns. These are called the train patterns. In the authentication or identification phases, the subject goes through the same process, but this time the ECG segments saved as ECG patterns are considered test patterns. These are compared with the train patterns available and the user is recognized if the k-smallest EDs between the test patterns and the train patterns are below a defined threshold. In summary, we perform pattern matching with a k-Nearest Neighbor (k-NN) classifier followed by a threshold test.

4 EXPERIMENTAL RESULTS & DISCUSSION

4.1 QRS Detection Performance

We implemented each of the QRS detection algorithms in Python and ran them with data from the Physionet database (Goldberger et al., 2000): the MIT-BIH Arrhythmia Database (MITDB) (Moody and Mark, 2001) which contains 48 half-hour ECG recordings from 47 subjects, and the MIT-BIH Noise Stress Test Database (NSTDB) (Moody et al., 1984) which consists of 12 half-hour ECG recordings.

Table 1 summarizes the QRS detection results (mean and standard deviation) for each of the previously presented QRS detection algorithms and for the two annotated databases used (column 1). The second column presents the algorithm's performance as measured by the ratio between the number of correct beats and the number of total detected beats (correct plus incorrect).

$$Performance = \frac{correctbeats}{incorrectbeats + correctbeats}$$

A detected beat is correct if it is within a 50ms tolerance interval from an annotated beat. Otherwise it is considered incorrect. The third column presents the correctly detected beats deviation error (DE), computed as the absolute value of the difference between the detected beat time instant and the annotated beat time instant. The fourth column presents the false positive results. It shows the mean and standard deviation values of the percentage of false positives, i.e., the ratio between the number of incorrect beats and the total number of detected beats. Below columns 2 to 4, there are 2 sub-columns indicating whether the results correspond to the algorithm on its own (Solo) or whether the results were evaluated using the majority criterion.

The QRS detection performance is above 90% for all five algorithms and the MITDB dataset. Also, all of them have a worse performance in the NSTDB dataset with the EZEEMod, HAM, and GAMBOA algorithms dropping to a performance around 75%, and the CHRIS and ESSF algorithms to around 85%. The deviation error is the lowest in the ESSF case with a mean of 3ms and 2ms for the MITDB and NSTDB datasets. The number of incorrect beats is below 10% in all cases and for the MITDB dataset and is higher

Table 1: QRS detection performance, deviation error and false positive results. Values are: mean±standard deviation.

Algorithm	**Performance (%)**		**Deviation Error (ms)**		**False Positives (%)**	
Database	**Solo**	**Majority**	**Solo**	**Majority**	**Solo**	**Majority**
EZEEMod						
MITDB	90.5±17.3	92.0±15.3	5.2±5.6	5.1±5.3	9.5±17.3	8.0±15.3
NSTDB	75.6±12.7	85.0±9.1	6.3±2.8	5.9±2.4	24.4±12.7	15.0±9.1
CHRIS						
MITDB	**94.3±7.8**	**93.3±12.6**	13.1±6.1	13.1±5.9	**5.7±7.8**	**6.7±12.6**
NSTDB	83.3±12.1	85.5±10.9	13.6±4.2	13.3±4.0	16.7±12.1	14.5±10.9
HAM						
MITDB	90.9±13.6	92.5±12.8	9.8±6.2	9.8±6.2	9.1±13.6	7.5±12.8
NSTDB	73.2±15.3	84.4±10.4	11.7±7.6	11.1±7.4	26.8±15.3	15.6±10.4
GAMBOA						
MITDB	92.3±13.2	92.6±13.1	14.3±17.0	14.3±17.0	7.7±13.2	7.4±13.1
NSTDB	74.1±30.2	74.9±30.5	18.3±17.2	18.3±17.2	25.9±30.2	25.1±30.5
ESSF						
MITDB	91.6±15.5	92.0±15.1	**3.4±3.9**	**3.4±3.9**	8.4±15.5	8.0±15.1
NSTDB	**88.8±7.2**	**89.8±7.3**	**2.3±1.1**	**2.2±1.2**	**11.2±7.2**	**10.2±7.3**

for the NSTDB dataset, ranging from 11% (ESSF) to 27% (CHRIS).

Overall, the CHRIS and ESSF algorithms correctly detects more beats, with the latter presenting a better accuracy with respect to the beat position. Also, the ESSF algorithm is the most robust one as the results with the two different datasets match more closely than in the other algorithms, and as it presents a better performance in the presence of noise (NSTDB dataset).

The application of the majority criterion reduces the number of false positives detected, which boosts performance (by increasing the ratio between correct beats and total detected beats) in all cases except one. In the CHRIS-MITDB, the case with higher performance in the solo mode, the majority voting decreased the number of true positives (correctly detected beats), and consequently decreased the performance, due to the fact that the majority of the other algorithms were not able to detect some of the beats detected with the CHRIS algorithm.

Table 2 complements Table 1 by presenting the results obtained using the unanimity criterion. In this case, each QRS complex detected is validated only if it was detected by all five algorithms. This reduces the number of false positives detected but also removes beats that were correctly detected by some algorithms but not all. The performance is similar to the mean value of the performances of each algorithm separately.

Table 3 also complements Table 1 by presenting the mean and standard deviation of the number of detected QRS complexes for each algorithm and dataset (MITDB and NSTDB), as well as the annotated data values (ANNOTATED).

Table 2: QRS detection results with the Unanimity criterion. Values are: mean±standard deviation.

Unanimity	MITDB	NSTDB
Performance (%)	93.8±12.7	79.0±29.7
False Positives (%)	6.2±12.7	21.0±29.7

4.2 Biometric Recognition Evaluation

In this case, a dataset previously collected by our group was used (Silva et al., 2011a). It is composed of data from 62 subjects (47 males and 15 females) with ages in the 31.1±9.46 range. The ECG data was collected from the subject's hands for approximately 2 minutes using Ag/AgCl electrodes. The ECG sensor is characterized by a gain of 1000 and an analog band pass filtering (1Hz to 30 Hz).

We used a subset of 31 individuals and choose this dataset as our interest is in hand ECG based biometrics. This allows us to test the biometric performance

Table 3: Mean and standard deviation of the number of detected QRS complexes.

Algorithm	QRS complexes	
	MITDB	NSTDB
ANNOTATED	2079.4±468.4	1854.5±311.5
EZEEMod	2176.0±493.0	2160.3±155.7
CHRIS	2162.5±389.9	2008.8±252.4
HAM	2275.8±429.6	2441.3±319.7
GAMBOA	2136.4±516.9	1526.1±694.6
ESSF	2114.3±588.8	1759.7±309.7

of the algorithms with signals acquired using a practical and non-intrusive procedure, in a biometrics point-of-view, and that have a lower signal-to-noise ratio (when compared with ECG signals acquired with a set of electrodes at the thorax). The QRS detection performance was not evaluated with this dataset as ground-truth annotations are not available.

We performed three experiences: one with ECG segments, one with mean waves of 3 ECG segments, and one with mean waves of 5 ECG segments. ECG segments for each individual were generated from the raw data, following the steps presented in Section 3. For each QRS detection algorithm, we created a dataset with these ECG segments and two other datasets in which each entry corresponds to a mean curve of (3 or 5) adjacent ECG segments. For each dataset constructed, the biometric recognition evaluation was performed 10 times using 60 random patterns for each individual (30 for training and 30 for test).

To measure the system's effectiveness, the False Acceptance Rate (FAR), False Rejection Rate (FRR), Receiver Operating Characteristic (ROC), and the Equal Error Rate (EER) measurements are commonly used. The FAR measures the rate at which a non-authorized individual is accepted; the FRR is the frequency at which the system rejects an authorized individual; the ROC plots the rate at which an authorized person is granted access (True Positive Rate) versus the FAR; and the EER is the rate at which the FRR equals the FAR. The EER is inversely proportional to the biometric system's accuracy: the lower the EER, the more accurate the system is.

4.2.1 Authentication

Table 4 presents the authentication results obtained. The performance is similar in all five algorithms and the EZEEMod and ESSF algorithms are the ones with the best results overall. This is justified by the fact that, as we saw in the previous section, these algorithms present higher accuracy with respect to the R-peak position detection, which is crucial for the segmentation step and the comparison between patterns. Furthermore, using mean waves, as opposed to single segments, presents better results in most cases (EER is lower in all cases except in the CHRIS case).

The recognition rates using the majority criterion are similar to the ones using the algorithm separately. This is justified with the fact that all algorithms have similar QRS detection results with this dataset as we observed posteriorly.

The unanimity criterion results compete with the best results obtained in all other cases: 5.8±0.5 (Unanimity-Segments) versus 5.7±0.3 (EZEEMod and SSF-Solo-Segments); 3.0±0.4 (Unanimity-Mean Waves of 3) versus 3.2±0.5 (EZEEMod-Solo-Mean Waves of 3); and 2.0±0.4 (Unanimity-Mean Waves of 5) versus 2.4±0.6 (SSF-Majority-Mean Waves of 5). Fig. 5 presents the FAR and FRR curves for the lowest EER obtained (Unanimity-Mean Waves of 5).

Table 4: Authentication results: mean and standard deviation of the EER for the 10 runs of the different trials performed.

Algorithm	EER (%)		
	Segments	Mean Waves of 3	Mean Waves of 5
EZEEMod			
Solo	**5.7±0.3**	3.2±0.5	2.5±0.7
Majority	6.2±0.4	3.4±0.3	3.0±0.5
CHRIS			
Solo	5.8±0.5	7.2±0.4	6.3±0.9
Majority	5.9±0.4	7.5±0.7	6.1±0.7
HAM			
Solo	5.8±0.3	3.7±0.4	3.1±0.6
Majority	6.0±0.4	3.9±0.4	3.4±0.6
GAMBOA			
Solo	5.7±0.4	5.6±0.6	4.7±1.1
Majority	5.7±0.5	5.2±0.6	4.3±1.0
ESSF			
Solo	**5.7±0.3**	3.5±0.3	2.5±0.5
Majority	5.8±0.4	3.5±0.3	2.4±0.6
Unanimity	5.8±0.5	**3.0±0.4**	**2.0±0.4**

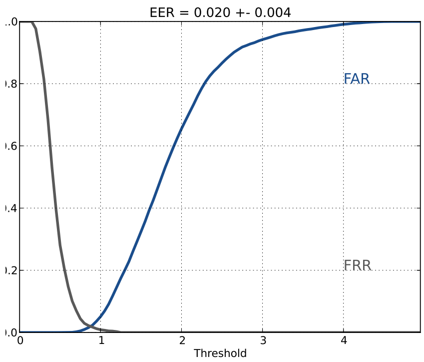


Figure 5: FAR and FRR curves obtained using the Unanimity criterion.

4.2.2 Identification

In the identification scenario, we evaluate the biometric system's performance by computing the identification error. Each time the system fails to correctly recognize a registered user is an identification error.

Identification results are presented in Table 5 and a similar analysis to the one performed before for the authentication scenario is used. As before, the error decreases as we switch from Segments to Mean Waves of 3 and to Mean Waves of 5, for the majority of the cases. Also, the use of the majority criterion yields results similar to the ones obtained by the algorithm on its own (Solo). When Segments are used, the results are around 5-6% and HAM (Solo) presents the lowest Identification Error: 5.0±1.1%. Using Mean Waves, the results improve (lower identification error) for all cases except for the CHRIS algorithm. Here, the algorithms EZEEMod (Majority) and Unanimity tie in first place: best result is 2.5±0.7%. The lowest identication error overall is obtained by applying the Unanimity criterion to Mean Waves of 5: 1.6±0.6%.

Table 5: Identification results: mean and standard deviation of the identification error for the 10 runs of the different trials performed.

Algorithm	Identification Error (%) Segments	Mean Waves of 3	Mean Waves of 5
EZEEMod			
Solo	5.8±1.1	2.8±0.9	2.1±0.7
Majority	5.5±0.8	**2.5±0.7**	2.1±0.7
CHRIS			
Solo	6.7±0.8	9.1±1.3	7.4±1.8
Majority	6.6±0.8	8.8±1.3	7.6±1.7
HAM			
Solo	**5.0±1.1**	3.6±1.0	3.3±1.5
Majority	5.1±1.2	4.0±0.8	3.5±1.1
GAMBOA			
Solo	6.2±0.8	4.7±1.1	3.1±1.3
Majority	5.1±1.1	3.8±0.8	3.0±1.0
ESSF			
Solo	5.1±1.3	3.1±0.8	2.4±1.2
Majority	5.3±1.1	2.9±0.8	2.3±1.1
Unanimity	5.6±1.0	**2.5±0.7**	**1.6±0.5**

5 CONCLUSIONS AND FUTURE WORK

We evaluated and compared five real-time segmentation algorithms with respect to their performance and biometric application. In future work, the warping effects, which results in the compression (expansion) of the ECG beat waveform due to higher (lower) heart rate should be considered and handled using adaptive segmentation limits, for example. We also plan to annotate the hand ECG dataset and re-run the beat detection performance tests to clearly know how each algorithm behaves with the hand ECG signals, which present a low signal-to-noise ratio, and high sensitivity to motion artifacts. About the biometric system, other pattern matching techniques should also be considered (e.g., using the cosine distance between patterns), as well as different values for the following parameters: number of mean waves, number of training patterns, and number of nearest neighbors used in the k-NN classifier.

All five evaluated algorithms run in real-time: the one by Hamilton, Gamboa, and the ESSF are simpler to implement; Christov's algorithm and the ESSF present higher robustness and beat detection performance; the Engelse and Zeelenberg's modified version and the ESSF are the ones with higher beat position accuracy. Overall, we were able to boost the QRS detection performance by combining the information from all algorithms in a voting manner - either by majority or unanimity.

For biometric recognition, combining the information from all algorithms with the unanimity criterion and using mean curves of adjacent 5 ECG segments results in the lowest error percentage: 2.0±0.4 and 1.6±0.5 for the authentication and identification scenarios, respectively.

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