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Comparative study of algorithms for ECG segmentation

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ABSTRACT

Accurate automatic identification of fiducial points within an ECG is required for the automatic interpretation of this signal. Several methods exist in the literature for automatic ECG segmentation. These algorithms are based on different methodologies and often evaluated with different datasets and protocols, which makes their performance challenging to compare.

For this study, nine segmentation algorithms were selected from the literature and evaluated with the same protocol in order to study their performance. One hundred signals from the PhysioNet's QT database were used for this evaluation.

Results showed that one of the algorithms based in the discrete wavelet transform achieved sensitivity of 100% when detecting the onset and offset of the QRS complex. An algorithm using the Multi-scale Morphological Derivate achieved sensitivities of 99.81%, 98.17% and 99.56% when detecting the peak, onset and offset respectively of the P-wave. When segmenting the T-wave, an algorithm based on the Phasor transform had a good performance with sensitivities of 97.78%, 97.81% and 95.43% when detecting the peak, onset and offset, respectively. Additionally, probabilistic methods such as Hidden Markov Models had good results due to the fact that they can learn from real signals and adapt to specific conditions. However, these techniques are often computationally more complex and require training.

This study could help in selecting optimal algorithms for ECG segmentation when implementing a system for automatic ECG interpretation.

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1. Introduction

Cardiac diseases are the primary cause of death in developed countries. Analysis of critical segments of the ECG is the most common technique for diagnostic and follow-up treatment for clinicians because it is non-invasive, inexpensive and safe [1]. Advanced computing systems and signal processing techniques permit the automatic interpretation of the ECG. In order for these systems to properly interpret ECG recordings, algorithms need to identify specific features accurately such as the location of the R-peak in order to analyse the cardiac rhythm. However, for more advanced automatic interpretation of the ECG signal, additional features need to be analysed including the length of the ST segment or the morphology of the different waves within the signal. This requires the implementation of algorithms that identify specific points within the ECG wave. Points of interest within the ECG include the start, peak, and end of the P, QRS, and T waves. The location of these points is plotted in Fig. 1.

There are several methods in the literature for segmenting the ECG. When selecting an algorithm to be used for a specific application, it is important to understand the performance as well as the characteristics of the different techniques available.

Automatic segmentation of the ECG is challenging. This is due to the high variability in the shape of the QRS complex, the reduced amplitude of the P-wave and the smooth transitions of the beginning and end of the T-wave. In addition, the lack of a universal consensus in the definition of the exact position of the fiducial points makes this task even more complex.

There are many methods in the literature for automatic ECG segmentation. Most of the methods address the detection of a limited number of the fiducial points within the ECG. Using the same method for detecting all fiducial points might be more challenging due to the different characteristics of the different ECG waves in terms of shape, frequency, amplitude and duration.

Most algorithms are based on two steps. In the first step, the ECG signal is transformed or filtered in order to highlight the relevant section of the ECG. This is often done by applying several filtering or transformation methods such as a low-pass differentiator [2,3], second-order derivatives [4–12], Fourier transform [13], wavelet transform [14–33], pattern recognition and correlation function

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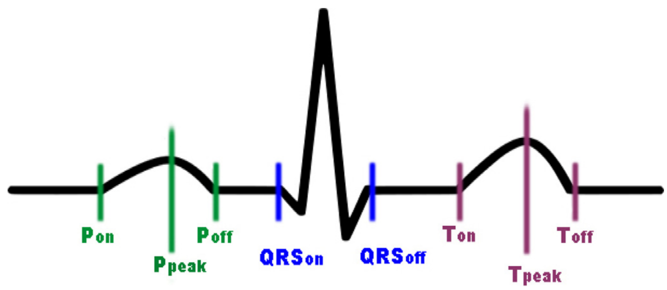

Fig. 1. Location of fiducial points to be identified by segmentation algorithms.

[7,31,34,35], Hilbert transform (HT) [12,32,33,36,37], piecewise linear approximations [38,39], multiple higher order moments [28], multiple-order derivative wavelet (MDWM) [32], multi-scale morphological derivate [40] and Phasor transform (PT) [41].

In the second step, the algorithm identifies and locates the points of interest by defining a set of rules. This is commonly achieved by the use of a heuristic approach based on an adaptive threshold [41–45]. Alternatively, some algorithms apply stochastic or probabilistic models, such as Hidden Markov (or Semi-Markov) Model [46–55], dynamic time warping (DTW) [38,39], artificial neural networks [27,56], evolutionary algorithms [18,29], best basis [57,58] and Bayesian techniques [56,59,60].

A direct comparison of segmentation algorithms from the literature is difficult due to the dissimilar methods and distinct datasets used for the algorithms evaluation. Therefore, a comparison study that quantifies the accuracy of several algorithms under similar conditions would provide a better understanding of their real performance.

In this work, we selected nine algorithms found in the literature that cover the most common signal processing techniques reported for ECG segmentation for further study. These algorithms were implemented following the instructions as reported in the literature and then evaluated with a dataset that is widely utilized in the field of ECG signal processing [61]. QRS-peak detection was not considered in this study as this topic has been widely studied in the literature [62–64].

2. Methods

2.1. Segmentation algorithms

Typically, algorithms for automatic ECG segmentation consist of two steps. In the first step, the input signal is conditioned or transformed and the main features of each wave are enhanced. In a second step, fiducial points are identified, often by applying heuristic rules making use of an adaptive threshold. Initially, the peak of the QRS complex is detected as a reference point, as it is the most prominent point within the ECG beat. The rest of the points of interest are found by a screening forward and backwards within delimited time windows around the QRS-peak. The positions of fiducial points are determined through adaptive thresholds. In one of the algorithms, a probabilistic method is used to identify fiducial points.

The algorithms selected for this comparative study are listed in Table 1 and briefly described in this section.

Laguna et al. [3]

The algorithm uses low-pass differentiation (LPD) to initially enhance the information of interest within the signal. The low-pass differentiator gives a filtered signal with information about the change in slope. Fiducial points are identified by using an adaptive threshold. The peaks of the waves of the original ECG signal are identified in the first derivative of the signal as zero crossings. The zero crossing is located between a positive and a negative deflection, representing a maximum in the original ECG signal. Wave limits (onset and offset) of the original signal are found by searching backward and forward from the detected peak on the transformed signal.

Martinez et al. [17]

The dyadic discrete wavelet transform (DWT) is used to transform the ECG signal into a time-scale domain in order to enhance the information from the QRS complex, P-wave and T-wave by filtering out noise and artifacts. In a second step, an adaptive threshold is applied to identify the fiducial points.

Singh et al. [42]

The algorithm uses both a recursive low-pass filter and the first derivative to enhance the signal. Then, lines from the peaks of the waves to the baseline are defined. The wave limits are determined by finding the maximum vertical offset from the signal to the defined lines.

Di Marco et al. [30]

The algorithm is designed for online processing and uses only two scales of the discrete wavelet transform (DWT), filtering out the rest. Then, an adaptive threshold is used for identification of the wave limits.

Sun et al. [40]

The algorithm uses a multi-scale morphological derivative (MMD) where the local maxima and minima are selected as potential fiducial points for both the peaks and the limits of the waves. Search windows are set in the transformed signal inside which a histogram is calculated to obtain an adaptive threshold value. Then, the wave peaks are identified by detecting the local maxima, and the wave limits are set as the nearest peaks (with opposite sign) that have an amplitude above the adaptive threshold.

Martinez et al. [41]

The algorithm transforms each instantaneous sample of ECG into a simple phasor, maximizing the different waves of the signal, and then the phase derivative is applied to find the limits of P and T waves. The maxima are identified as peaks of the P and T waves, while the zero crossings of the phasor derivative function are set as the limits of these waves.

Vazquez et al. [43]

The algorithm uses a band-pass Butterworth filter and the first derivative. After filtering, the authors proposed a geometric method in which a rectangular trapezium is continuously calculated once the wave peak is detected, using three fixed vertices and one mobile or variable vertex. The limits of the waves under examination are deemed to correspond to the point of the mobile vertex, where the area of the trapezium is a maximum.

Vítek et al. [26]

The algorithm uses the continuous wavelet transform (CWT), where each fiducial point is determined by applying an adaptive threshold in the corresponding CWT scale according to the fundamental frequency of the wave.

Hughes et al. [52]

The algorithm uses the discrete wavelet transform (DWT) and then a HMM that is trained in a supervised manner to identify the fiducial points of interest.

2.2. Database

The PhysioNet's QT database (QTDB) [65] was utilized for the evaluation of the aforementioned algorithms. This dataset contains a compilation of 105 recordings selected from other ECG databases and represents a wide variety of QRS, T- and P-wave morphologies. Each recording contains 2 leads and has a length of 15 min with a sampling frequency of 250 Hz. At least 30 beats from each record were manually annotated by an expert. In addition, 11 of the recordings were annotated by a second expert. The annotations available

Table 1
Studied methods.

Author	*Method*	
Laguna [3]	- Low Pass Differentiation (LPD)	Adaptive threshold based (Heuristic rules)
Martinez [17]	- Discrete Wavelet Transform (DWT)	
Singh [42]	- Recursive low-pass filter and a differentiator - Adaptive threshold: Position where vertical offset in maximum	
Di Marco [30]	- Discrete Wavelet Transform (DWT)	
Sun [40]	- Multi-scale Morphological Derivate (MMD) - Adaptive threshold with histogram information	
Martinez [41]	- Phasor Transform (PT)	
Vazquez [43]	- Band-pass Butterworth filter and the first derivative - Adaptive threshold: rectangular trapezium area	
Vítek [26]	- Continuous Wavelet Transform (CWT)	
Hughes [52]	- Discrete Wavelet Transform (DWT) - Hidden Markov Model (HMM)	Probabilistic models

in this database are the peak, onset and offset of both the QRS complex (QRS_{peak}, QRS_{on}, QRS_{off}) and P-wave (P_{peak}, P_{on}, P_{off}) as well as the peak and offset of the T-wave (T_{peak}, T_{off}). The onset of the T-wave (T_{on}) was annotated only in some of the records (with a total of 1345 beats).

One hundred of the 105 recordings were considered in this work. Records *sel35*, *sel50*, *sel37*, *sel44* and *sel232* were discarded as they do not include annotations for the QRS_{peak}. Since manual annotations were common for both leads, algorithms were applied on both leads separately, and only the detection closest to the manual annotation was considered.

The algorithm developed by Hughes et al. [52] requires a training step. This was done by using the first five beats of each signal of the dataset.

2.3. Evaluation criteria

In order to measure the performance of the segmentation algorithms under review, the average value (μ) and the standard deviation (σ) of the difference (i.e. the notional *error*) between the algorithm output and the annotation were calculated. A difference greater than 120 ms between the annotation and the algorithm output was considered to be a missed detection. The sensitivity (Se) was also calculated to quantify the missed detections. As the threshold for considering a true detection was high, and non-detected points were not included in the error determination, Se and error should be interpreted together.

Additionally, a criteria as described by Jane and colleagues [5] was considered for evaluation. The output of the algorithm under review for each recording was classified into one of 4 groups depending on the error (μ and σ) obtained. These 4 groups were defined in the following way: Group 1) acceptable μ and σ, Group 2) acceptable σ but non-acceptable μ, Group 3) acceptable μ but non-acceptable σ, and Group 4) unacceptable μ and σ (Table 2). An acceptable μ error was considered to be 15 ms as suggested by Sörnmo and Laguna [2]. Acceptable σ error values were different for each fiducial point and defined following the recommendations of the CSE Working Party [66]. The acceptable σ error values corresponding to the onset and offset for the P-wave were 10.2 ms and 12.7 ms respectively, and for the QRS were 6.5 ms and 11.6 ms respectively. The acceptable σ error for the offset of the T-wave was 30.6 ms (Table 3). The percentage of recordings classified in Group 1 (i.e. acceptable μ and σ) was also calculated as a measurement of the performance of the algorithms under review.

Table 3
Values for acceptable σ errors.

	P_{on}	P_{off}	QRS_{on}	QRS_{off}	T_{off}
$\sigma_{accepted}$(ms)	10.2	12.7	6.5	11.6	30.6

Some of the algorithms were designed for locating specific waves, In this study, the algorithms were only tested for their desired purpose.

2.4. Computing time

The computational cost for each algorithm was determined by calculating the time required to analyse a signal of 5 min length. Ten different ECG signals where used and the average and standard deviation of the computing time was calculated. The algorithms were executed in Matlab (2010b) running on a computer with the OS X operating system, 2.53 GHz Intel Core 2 Duo processor and 8 GB of RAM memory.

3. Results

Table 4 shows the results obtained after evaluation of the 9 algorithms on the QT database. The percentage of records classified within Group 1 (i.e. records that obtained a good detection with acceptable μ and σ) are also presented. When available, the results obtained in our study are shown together with the results reported in literature (in brackets).

3.1. QRS complex

The QRS complex is the most prominent wave within the ECG and therefore, all segmentation algorithms had high sensitivity (Se) values (above 99%) when detecting both QRS_{on} and QRS_{off}.

The best results detecting QRS_{on} were obtained by both Martinez et al. [17] and Hughes et al. [52]. The first technique [17] resulted in the lowest error (-1.4 ± 7.6 ms) with 50% of the records classified into Group 1. The second algorithm [52] had the highest percentage of records within Group 1 (60%), but a larger error (2.4 ± 6.5 ms).

Table 2
Group classification and their characteristics.

Group 1	$\mu < 15$(ms)	$\sigma < \sigma_{accepted}$(ms)	Registers with good detection (reasonable μ and σ).
Group 2	$\mu > 15$(ms)	$\sigma < \sigma_{accepted}$(ms)	Often morphology identification errors, commonly systematic errors.
Group 3	$\mu < 15$(ms)	$\sigma > \sigma_{accepted}$(ms)	Usually signals with poor SNR due to noise or small wave's amplitude.
Group 4	$\mu > 15$(ms)	$\sigma > \sigma_{accepted}$(ms)	Combination of characteristics of groups 2 and 3. Morphology identification error together with poor SNR.

Table 4
Results of the evaluation of the segmentation algorithms under review. All, Se (%), error ($\mu \pm \sigma$ (ms)) and percentage of records classified within Group 1 (G1) are obtained for each fiducial point. For comparison, in parentheses the results as reported by the authors in the literature are shown.

		P_{on}	P_{peak}	P_{off}	ORS_{on}	ORS_{off}	T_{on}	T_{peak}	T_{off}
	Se (%)	94.04	97.26	98.04	99.94	99.71	95.09	95.61	94.50
Laguna [3]		(97.70)	(97.70)	(97.70)	(99.92)	(99.92)		(99.00)	(99.00)
	$\mu\pm\sigma$ (ms)	11.3±14.6	11.1±11.6	5.4±13.7	12.1±18.4	5.3±10.2	14.1±25.8	2.1±12.9	6.8±18.4
		(14.0±13.3)	(4.8±10.6)	(−0.1±12.3)	(−3.6±8.6)	(−1.1±8.3)		(−7.2±14.3)	(135±27.0)
	Gl (%)	45.83	54.17	61.46	40.00	49.00	44.19	61.90	69.47
	Se (%)	97.48	99.49	99.46	100.00	100.00	95.32	97.48	94.50
Martinez [17]		(98.87)	(98.87)	(98.75)	(99.97)	(99.97)		(99.77)	(99.77)
	$\mu\pm\sigma$ (ms)	−12.4±14.4	−3.7±11.5	−8.4±13.3	−1.4±7.6	1.9±8.4	14.4±21.3	0.7±12.1	−11.9±16.6
		(2.0±14.8)	(3.6±13.2)	(1.9±12.8)	(4.6±7.7)	(0.8±8.7)		(0.2±13.9)	(−1.6±18.1)
	Gl (%)	29.47	60.41	47.92	51.00	82.00	40.47	56.12	65.62
	Se (%)	97.70	95.99	99.05			79.98	91.02	87.80
Singh [42]	$\mu\pm\sigma$ (ms)	9.1±25.3	13.1±14.9	−7.4±17.2			34.4±27.8	14.4±6.8	33.7±225
		(5.18±8.1)		(4.4±6.3)			(4.4±6.3)		
	Gl (%)	5.21	40.62	39.58			9.75	1.06	7.45
	Se (%)	97.88	97.98	98.45	100.00	100.00	93.43	97.31	96.43
Di Marco [30]		(98.15)	(98.15)	(9815)	(100)	(100)		(99.72)	(99.77)
	$\mu\pm\sigma$ (ms)	1.2±15.9	7.1±12.9	2.9±15.3	6.6±9.5	1.7±8.5	5.8±232	1.9±12.8	2.9±18.5
		(−4.5±13.4)	(−4.7±9.7)	(−2.5±13.0)	(−5.1±7.2)	(0.9±8.7)		(−0.3±12.8)	(1.3±18.6)
	Gl (%)	56.25	55.2 1	61.46	41.00	81.00	58.14	53.53	77.78
	Se (%)	98.17	99.81	99.56	100.00	100.00	97.73	96.75	89.88
Sun [40]		(97.2)		(94.8)	(100)	(100)	(99.8)		(99.6)
	$\mu\pm\sigma$ (ms)	9.4±18.4		3.7±18.8	7.6±11.8	−2.5±9.8	11.5±23.9	−0.7±12.6	9.4±28.6
		(9.0±9.4)		(12.8±13.2)	(3.5±6.1)	(2.4±10.3)	(7.9±15.8)		(8.3±12.4)
	Gl (%)	32.29	65.62	2917	15.00	68.00	34.88	58.16	40.40
	Se (%)	96.91	97.82	98.26	100.00	100.00	97.81	97.78	95.43
Martinez [41]		(98.65)	(98.65)	(98.65)	(99.85)	(99.85)	(99.20)	(99.20)	(99.20)
	$\mu\pm\sigma$ (ms)	9.4±19.5	4.5±10.9	−3.9±15.1	2.9±11.0	6.8±10.6	8.3±30.4	0.8±14.1	−13.9±22.5
		(2.6±14.5)	(32±25.7)	(0.7±14.7)	(−0.2±7.2)	(2.5±8.9)		(5.3±12.9)	(5.8±22.7)
	Gl (%)	31.25	50.00	55.21	5.00	64.00	23.26	46.46	45.45
	Se (%)	98.93	99.78	99.72	100.00	100.00	93.28	96.81	96.02
Vazquez [43]	$\mu\pm\sigma$ (ms)	5.6±17.7	3.2±15.2	−6.7±15.2	3.1±7.1	3.2±8.4	14.7±24.3	7.4±13.8	4.0±19.0
	Gl (%)	35.42	30.21	50.00	47.00	81.00	51.16	49.49	77.78
	Se (%)	97.35	99.34	99.68	100.00	100.00	93.50	92.13	90.58
Vitek [26]	$\mu\pm\sigma$ (ms)	7.5±14.7	5.0±12.3	13.1±14.7	2.2±7.5	−0.1±8.5	1.3±29.8	5.2±17.4	8.2±20.9
	Gl (%)	42.71	51.04	23.96	48.00	82.00	42.86	48.45	55.67
	Se (%)	96.50		98.45	100.00	99.48			95.29
Hughes [52]	$\mu\pm\sigma$ (ms)	−1.4±14.2		1.1±11.6	2.4±6.5	−4.1±8.9			−9.7±19.8
	Gl (%)	57.89		72.91	60.00	76.00			59.60

Algorithms Vítek et al. [26], Martinez et al. [17] and Di Marco et al. [30] that use the wavelet transform, obtained the best results for detecting the QRS_{off} fiducial point. All three algorithms had a standard deviation (σ) of approximately 2 samples (8 ms) and an average error (μ) of less than 2 ms. Regarding group classification, all of them achieved more than 80% of classifications into Group 1.

Fig. 2 shows the results in box plot format. The average error and standard deviation of each algorithm and for each fiducial point are highlighted.

3.2. P-wave

The P-wave has the lowest amplitude within the normal ECG and therefore is often the most difficult to segment. When detecting P_{peak}, the method from Sun et al. [40] had the highest Se (99.81%) and percentage of records classified in Group 1 (65.6%). With regard to the results obtained for detecting P_{on}, the segmentation method developed by Di Marco et al. [30] obtained one of the best results with an average error of 1.2 ms and a standard deviation of 15.9 ms. Also, the Se was high (97.88%) and the percentage of records within Group 1 was 56.25%. The method developed by Hughes et al. [52] had similar results with regard to the error, and although the Se was lower (96.50%), the percentage of records classified in Group 1 was higher (57.89%). Vazquez et al. [43] was the method with the highest Se (98.93%), however, it gave a larger error compared to both Di Marco and Hughes (5.6 ± 17.7 ms).

Vazquez et al. [43] provided the highest Se when detecting P_{off} (99.72%), while the lowest error was obtained by Hughes et al. [52] (1.1 ± 11.6 ms). In addition, this method had the highest percentage of data classified into Group 1 (72.91%).

Fig. 3 shows the results in box plot format. The average error and standard deviation of each algorithm and for each fiducial point are highlighted.

3.3. T-wave

Interestingly, although the amplitude of the T-wave is significantly larger when compared to the P-wave, segmentation of this wave did not lead to better results when segmenting this wave.

Regarding T_{peak}, the method that had the best performance was Martinez et al. [17] with a Se = 97.48% and error = 0.7 ± 12.1 ms. Di Marco et al. [30] obtained similar results (Se = 97.31%, error = 1.9 ± 12.8 ms), while Martinez et al. [41] achieved slightly higher Se (97.78%). Although Laguna et al. [3] had lowest Se (95.61%), it had the highest percentage of records classified into Group 1 (61.9%).

When detecting the onset of the T-wave (T_{on}) the highest Se was obtained with the method from Martinez et al. [41] (97.81%). Di Marco et al. [30] had the highest percentage of records classified in Group 1 (58.14%).

The offset of the T-wave is often difficult to identify visually. Therefore, errors between the manual annotations and output of the algorithms were higher as compared to other fiducial points. The best results were obtained with the methods of Vazquez et al. [43] (Se = 96.02%, error = 3.9 ± 18.9 ms) and Di Marco et al. [30] (Se = 96.43%, and error = 2.9 ± 18.5 ms). These two techniques also

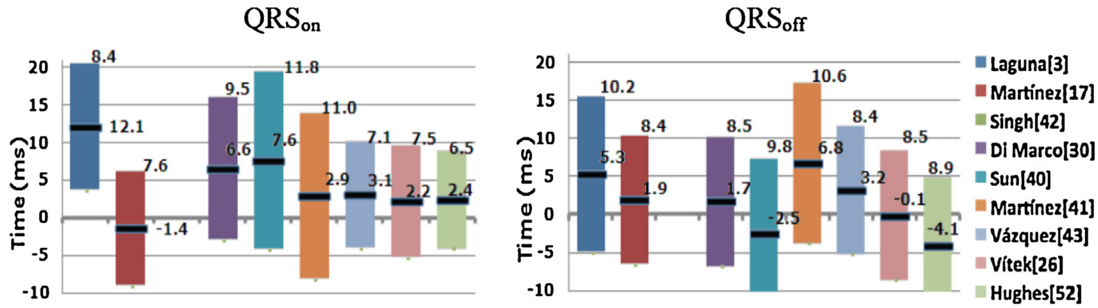

Fig. 2. Each boxplot shows the result of the error obtained with each algorithm for QRS detection. The boxplot is centred on the average error (μ) and its length represents its standard deviation (σ) in ms.

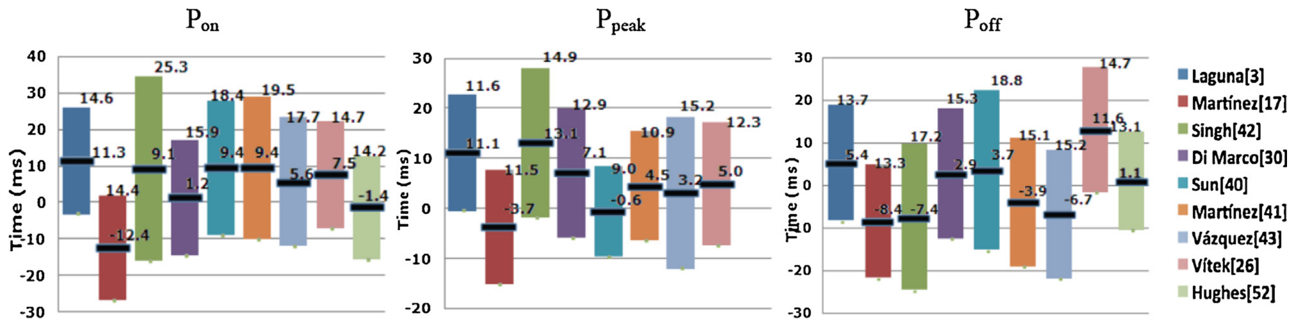

Fig. 3. Each boxplot shows the result of the error obtained with each algorithm for P wave detection. The boxplot is centred on the average error (μ) and its length represents its standard deviation (σ) in ms.

had the highest percentage of records classified within Group 1 (both with 77.78%).

Fig. 4 shows the results in box plot format. The average error and standard deviation of each algorithm and for each fiducial point are highlighted.

3.4. Computing time

The algorithm with a lowest computing time was Laguna et al. [3], which uses a derivative and required 1.04 ± 0.35 s for the segmentation of an ECG with 5 min length. The algorithm with the highest computing time was Sun et al. [40] which required 109.44 ± 9.08 s. This is due to the high computational cost of calculating the Multi-scale Morphological Derivative and the calculation of the threshold by using a histogram for each fiducial point. The computing time for each algorithm is shown in Table 5.

4. Discussion

This study reviews the performance of nine algorithms for the segmentation of the waves within the ECG. The outcome could be significantly relevant when designing a system that requires the automatic interpretation of this cardiac signal. In order to compare these algorithms, the same database and evaluation criteria were used. Some of the methods studied were designed for the detection of specific waves within the ECG, therefore in those methods only the fiducial points for which the algorithm was designed, were considered. Fig. 5 shows the algorithm that had the best performance for each fiducial point.

Methods based on the wavelet transform (WT) were shown to have a good performance. This is probably due to the fact that wavelets can adapt well to the morphology of the waves within the ECG signal [63]. In addition, by extracting features in the time-scale domain, no pre-filtering is required.

Sun et al. [40] developed a method that obtained good results in the annotation of the peaks of both the P and T-wave. The morphological filter used in this method is robust against baseline wander noise.

The algorithm developed by Di Marco et al. [30], which is based on WT, might be a good option for segmentation. Although it did not give the best results overall, this method still has good performance by using only 2 scales of the WT and applying thresholds that are calculated through few local coefficients. Taking into account that it does not use many parameters the results are significantly good.

The algorithm based on the calculation of trapezium areas proposed by Vazquez et al. [43] was a good technique for determining both the onset of the P-wave and the offset of the T-wave, both in terms of the quality of results and an acceptable computing cost.

Probabilistic methods such as Hidden Markov Models offer significant improvements over the heuristic methods since they can learn from real signals and adapt to specific conditions. The method proposed by Hughes et al. [52] did not obtain a good performance in terms of Se as compared to the rest of the algorithms. However, it classified a high percentage of records into Group 1. It also obtained low error values, reflecting high accuracy when detecting fiducial points. However, probabilistic methods might be computationally more complex as they require training.

Computational cost might have a higher or lower importance for different applications. In the case of ambulatory devices where computational power is limited and real-time analysis is required,

Table 5
Computing time required for each algorithm to analyse an ECG signals of 5 min length.

Laguna [3]	1.04 ± 0.35 s
Martinez [17]	7.12 ± 1.50 s
Singh [42]	10.28 ± 1.13 s
Di Marco [30]	5.06 ± 1.20 s
Sun [40]	109.44 ± 9.08 s
Martinez [41]	57.83 ± 4.91 s
Vazquez [43]	6.16 ± 1.59 s
Vítek [26]	6.67 ± 1.63 s
Hughes [52]	45.65 ± 3.00 s

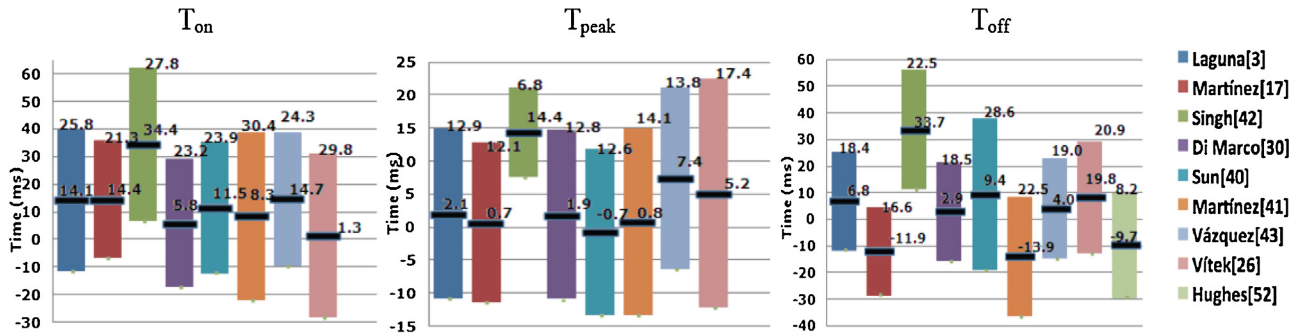

Fig. 4. Each boxplot shows the result of the error obtained with each algorithm for T wave detection. The boxplot is centred on the average error (μ) and its length represents its standard deviation (σ) in ms.

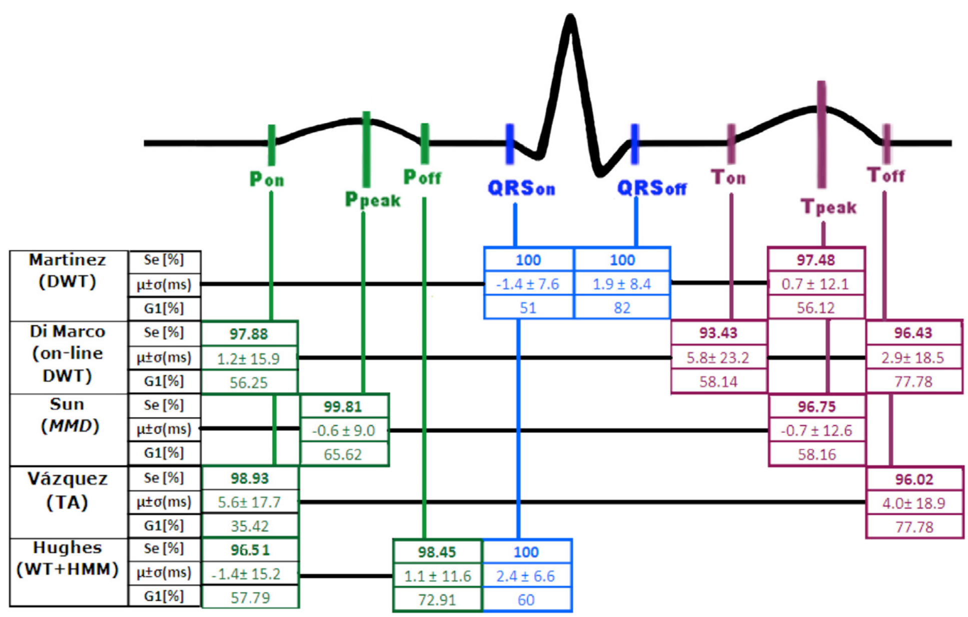

Fig. 5. Summary of algorithms that showed best results for each fiducial point.

a low computational complexity algorithm might be preferred. In contrast, in non-ambulatory conditions, algorithm detection accuracy might be preferred while computational cost would be less critical. In our study, the algorithm with the lowest computing cost was Laguna et al. [3] which required about a second to analyse an ECG signal of 5 min length. Algorithms based on band pass filters or wavelet transform had in general low cost, with computing times below 10 s, with the exception of Hughes et al. [52] that despite using DWT required significantly longer time due to the use of a probabilistic method.

To the authors' knowledge, this is the first study that compares a significant number of algorithms for ECG segmentation under similar conditions. The results of this study will help to understand the differences of the different techniques investigated as well as to help in the selection when designing a clinical application that requires the implementation of an algorithm for automatic interpretation of an ECG signal.

The results obtained in this study were consistent with those reported in the literature, especially for the segmentation of the QRS wave. These were less consistent when segmenting the T-wave in which the results obtained in our study were slightly worse than those reported in the literature. For some algorithms, the performance was not reported.

One limitation of this study to be considered is that the code implemented by the authors of the algorithms selected for study was not available. Therefore, the algorithms were implemented following the instructions reported by the authors in their publications. Although an accurate implementation of each algorithm was attempted, code differences might have occurred between the original implementation and the one in this study.

5. Conclusions

This paper reviews the performance of nine algorithms for the segmentation of the waves within the ECG. Results showed that methods based on the wavelet transform had a good performance. Also, probabilistic methods such as Hidden Markov Models had good results due to the fact that they can learn from real signals and adapt to specific conditions. Heuristic methods have a significantly lower computational cost than probabilistic methods.

Conflict of interest

The authors declare that they have no conflict of interest.

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