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Robust Beat Detector for Ambulatory Cardiac Monitoring

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***Abstract*—Robust beat detection under noisy conditions is required in order to obtain a correct clinical interpretation of the ECG in ambulatory settings. This paper describes the evaluation and optimization of a beat detection algorithm that is robust against high levels of noise. An evaluation protocol is defined in order to study four different characteristics of the algorithm: *non-rhythmic patterns, different levels of SNR, exact peak detection and different levels of physical activity*. This protocol is based on the MIT/BIH arrhythmia database and additional ECG recordings obtained under different levels of physical activity measured by 2-axis accelerometers. The optimized algorithm obtained a *Se=99.65%* and *+P=99.79%* on the MIT/BIH arrhythmia database while keeping a good performance on ECGs with high levels of activity (overall of *Se=99.86%*, *+P=99.91%*). In addition, this method was optimized to work in real time, for future implementation in a Wireless ECG sensor based on a microprocessor.**

I. Introduction

THE fast improvement of microelectronics and computational systems have lead to the design of portable devices that permit the ambulatory recording of ECG signals during routinary life. These devices have been improved drastically in the last years by reduction of weight, size and energy consumption, while the available computational power has been increased. As they get more power efficient, they permit ECG monitoring over longer periods of time. The increased computational power enables execution of more complex algorithms, giving the opportunity to use new advanced techniques of signal processing. This permits the automatic analysis of cardiac signals leading to several clinical applications such as arrhythmia detection. This is still challenging, due to the fact that the algorithms embedded in portable devices need to comply certain requirements in order to meet the memory and complexity limitations of the microprocessors.

One of the most targeted problems in the automatic analysis of ECG signals is the detection of the QRS complex, also known as beat detection [1]. Many algorithms have been developed for this purpose and different techniques have been used for this problem. Among these techniques are Time Domain methods, such as Zero-Crossing [2] and Signal Derivatives [3], Digital Filters [4], Filter Banks [5], Neural Networks [6] and Wavelet Analysis [7, 8]. These methods give satisfactory results with detection rates quite over 99 % while used in hospital conditions.

For ambulatory monitoring the challenge of beat detection increases as the level of noise and motion artifacts is considerably higher than for hospital monitoring. Such an environment calls for algorithms that are robust against the noise induced by daily-life activities while maintaining a high level of accuracy. This should also take into account the computational complexity and memory in addition to the numerical resolution that typically have more limitations in portable devices.

This paper describes the optimization of a method for beat detection based on the Continuous Wavelet Transform (CWT) [8]. This algorithm was optimized to work in real time and under reasonable levels of noise due to movement. With that aim, we propose a protocol for studying the performance of the algorithm by measuring different parameters that are related to real life activity. The final objective is the hardware implementation of the algorithm in the microprocessor of a future wireless ambulatory cardiac monitor.

II. Methods

A. Beat Detection Algorithms

Three methods for beat detection were selected for further investigation. The first algorithm considered was a Time-Domain method (TD) which was based on the method published in 1985 by J. Pan and W.J. Tompkins [9]. This method was found to have a well-balanced trade-off between detection performance and computational complexity, which could make it a good technique to embed in a microcontroller. A second candidate was an algorithm based on the Discrete Wavelet Transform (DWT) developed by J.P. Martinez et al. [10]. Wavelets were selected as they work as filter banks and hence provide robustness against noise. The Continuous Wavelet Transform (CWT) provides more flexibility in the filter bank design, and can thus be matched to the properties of the different components of interest within a beat. Therefore, a method based on this technique and developed by I. Romero et al. [8] was also investigated.

B. CWT Algorithm Optimization

Romero's algorithm [8] was originally tested and developed with ECG signals recorded in hospital where levels of noise and artifacts are significantly lower than the levels recorded during ambulatory monitoring. The

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algorithm was implemented following the scheme as described in the publication (Fig. 1) and further optimized, taking into account that the final application will be an ambulatory device. With this aim, several changes were investigated.

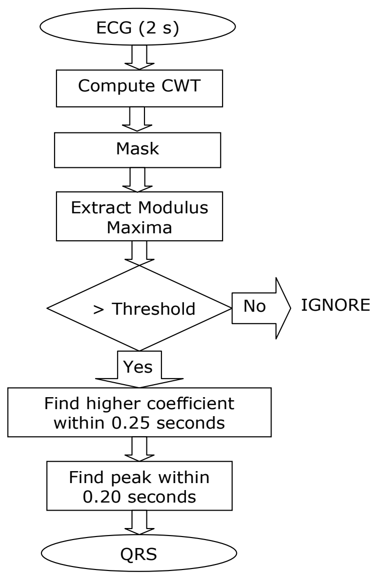

Fig. 1. Scheme of the CWT algorithm developed by Romero et al. [8].

The modulus maxima algorithm relates the peak detection to the maximum value within the analysis window, and hence it is very sensitive to peaks in the CWT domain that can occur due to transitional high levels of noise. To avoid this, the threshold (th_{new}) was computed recursively – by using a weighted sum of the previous threshold (th_{old}) and the newly calculated threshold ($th_{current}$) as in (1).

$$th_{new} = w \cdot th_{old} + (1 - w) \cdot th_{current} \tag{1}$$

Several weights ($0 \leq w < 1$) were investigated to find the optimal values. In the original algorithm, possible beats were considered as soon as the threshold is exceeded in one of the wavelet scales. A more stringent condition can be defined so that a beat must exceed the threshold in at least N out of K scales.

Finally, the possibility of re-adapting the threshold in function of the heart rhythm was also investigated. In this implementation, the threshold is changed in case of abrupt changes in rhythm, in order to verify whether the rhythm change is due to a change in cardiac activity or to false detections as a result of noise.

C. Evaluation Protocol

For evaluating the different versions of the algorithms a set of tests was developed that permits the evaluation of the performance as a function of a wide range of conditions. This test protocol was then used for benchmarking the different methods and to study the improvement of the optimization steps.

In the first part of the test the MIT/BIH arrhythmia database was used. This database is considered as a standard dataset widely used for beat detection algorithm testing. It permits the comparison of different methods, and contains a wide spectrum of different rhythmic and pathological patterns that can be observed in clinical practice.

A second part of our test protocol aimed to study the robustness against noise. Signal 100 from the MIT/BIH dataset was selected for having a very clean ECG signal. To simulate different levels of noise, a noise signal obtained from the MIT-BIH Noise Stress Test Database was added to this clean ECG. A range of SNR varying from -10 to 10 dB in steps of 1 dB was considered. The noise signal *em* was used, to mimic electrode motion artifact – that is considered to be the most relevant source of noise in an ambulatory monitoring setting.

As high accuracy in time is typically required for several applications on ECG analysis (such as Heart Rate Variability, Synchronous Averaging) we also propose a third test, where the accuracy of the algorithm in detection the exact R-peak was investigated. Two hours of data obtained from in-house recorded signals were annotated. For this test a sample frequency of 1000 Hz was used in order to obtain a more accurate time resolution.

Finally, in order to test the performance of an algorithm under different levels of activity in true ambulatory conditions, a set of ECGs were recorded using wireless ECG devices developed by our research group [11]. Ten healthy subjects were selected. For each volunteer, recordings of 10 minutes length were obtained in 3 levels of activity: low level activity: sitting at the desk, medium level of activity: biking on a static bike at 70 rpm and 100 Watts, and high level of activity: running on a treadmill at 7.5 km/h. The cardiac activity was recorded using our flexible ECG Patch [11], [12], attached to the chest of the subject using standard lead positions I and II. In order to quantify the level of body movement, a 2-dimensional accelerometer was incorporated to the ECG sensor. The modulus of the vector formed by the two directions was obtained and the RMS value after subtracting the DC component was calculated as a reference of the motion level (Fig. 2). The sample frequency of the signals was 198 Hz. The ECG signals were manually annotated in order to mark the QRS complex. The peak of the R wave was considered as the fiducial point for the annotations. The time intervals where the SNR was too low

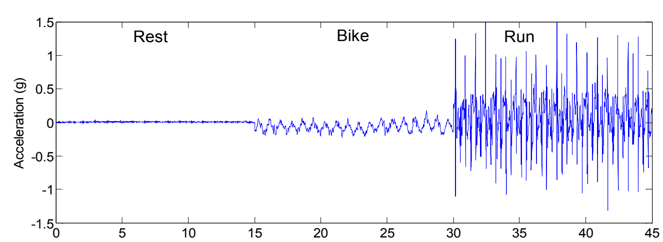

Fig. 2. Output signal measured by an accelerometer placed at the chest under three levels of activity.

for manual annotation were excluded of any further study. In total, 45 records were considered with a duration of 10 minutes each.

III. Results

A. Algorithm comparison on MIT/BIH Arrhythmia database

It was found that the TD algorithm has a very high positive predictivity. However, it can be sensitive to sudden changes in heart rhythm which decreases its sensitivity. The DWT algorithm is quite sensitive to noise, which is relatively often detected as a peak which gives a high number of false positives and therefore low positive predictivity. The algorithm based on the CWT outperformed the other two methods giving a total Sensitivity of 99.64% and Positive Predictivity of 99.65%. The performance of the algorithms on the MIT/BIH can be seen in Table I.

TABLE I
Beat Detector Results on MIT/BIH database

	TD		DWT		CWT	
Signal	Se	+P	Se	+P	Se	+P
100	99.96	100.00	100.00	99.96	100.00	99.96
101	99.95	99.84	99.95	98.36	99.95	99.73
102	100.00	100.00	99.73	99.63	100.00	100.00
103	99.81	100.00	100.00	99.95	99.95	100.00
104	99.87	98.23	99.46	85.86	99.87	97.03
105	99.69	98.12	98.83	94.22	99.42	97.89
106	98.22	99.85	97.39	99.15	98.62	100.00
107	99.86	100.00	99.77	99.81	99.72	99.91
118	100.00	99.74	99.96	95.99	99.96	99.78
119	100.00	100.00	97.48	95.70	100.00	99.90
200	99.85	99.31	98.62	89.72	99.92	99.85
201	96.33	99.95	98.88	99.44	100.00	99.59
202	99.86	99.58	98.50	97.32	99.86	99.95
203	92.48	98.96	94.93	87.99	97.72	98.91
205	99.25	100.00	99.10	99.77	99.85	100.00
208	67.03	99.85	87.65	98.14	99.32	99.83
209	98.17	100.00	99.90	98.46	100.00	100.00
210	96.07	97.51	99.09	96.44	98.45	99.77
212	99.89	100.00	100.00	98.78	99.96	100.00
213	99.69	100.00	99.42	99.88	99.97	99.97
214	99.73	99.91	99.29	98.86	99.78	99.96
215	99.49	100.00	99.85	99.29	99.97	99.85
217	99.59	99.91	99.41	99.68	99.64	99.86
219	99.49	100.00	99.86	100.00	100.00	100.00
	97.32	**99.60**	**98.51**	**96.96**	**99.64**	**99.65**

B. Algorithm Evaluation

The results of the test for robustness to noise are plotted in Fig. 3. Analyzing the sensitivity of the three methods, it can be observed that all methods score very well at SNR levels above 5 dB. At SNR levels below 5 dB, the performance of DWT decrements, while TD and CWT keep a high sensitivity down to a SNR of 0 dB. Below 0 dB, the sensitivity of both CWT and TD quickly decreases.

In terms of positive predictivity TD has a significantly better performance while CWT and DWT have a similar behavior with a fast decrement below 7 dB.

For the accuracy of the exact R-peak detection it was observed that the CWT obtains a high accuracy with an averaged deviation of 0.03 ms per beat (99.9% of the beats were detected with perfect accuracy), while TD and the DWT have an averaged deviation of 9.79 ms (with 19.2% of the beats detected perfectly) and 71.74 ms (with 25.9% of the beats detected perfectly), respectively.

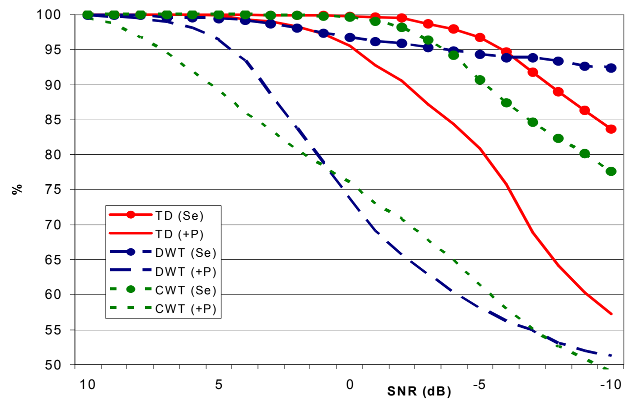

Fig. 3. Noise Test Results.

Finally, the algorithms were tested with signals collected during three different activities. The level of activity measured by accelerometers were in median 0.26 m/s^2 at work, 0.71 m/s^2 on biking and 5.57 m/s^2 when the activity was running. CWT had again the best performance with a Sensitivity and Positive Predictivity close to 100% for all the activities. TD had a high positive predictivity however the sensitivity decreased significantly when the activity level increased. DWT had opposite performance with high sensitivity and low positive predictivity in noisy conditions. The results are plotted in Fig. 4.

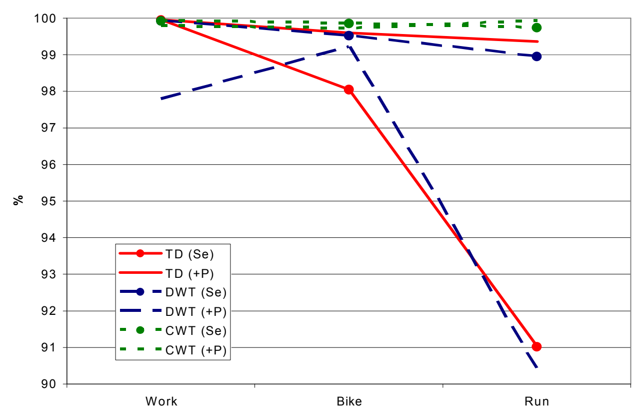

Fig. 4. Activity Test Results.

After observing these results, it was concluded that the CWT algorithm had an overall good performance. However it was still not so robust under high noise conditions (Fig. 3). This algorithm was therefore selected for further optimization.

C. CWT Algorithm Optimization

With the aim of obtaining a better performance, several changes were proposed to the original version of the CWT algorithm and evaluated following the evaluation protocol.

First, (*Step 1*) it was found that equal weighting (w=0.5 in

(1)) gave best results on the MIT/BIH database. As a second step (*Step 2*), the threshold was applied on several wavelet scales and only when exceeded in at least 2 scales, possible beats were considered. Finally, (*Step 3*) the possibility of re-adapting the threshold in function of the heart rhythm was investigated. As the original algorithm showed very good performance in accurately detecting R-peaks, no changes were proposed in this sense and therefore, the R-peak test did not show any changes. Fig. 5 shows the results obtained for the evaluation of the different optimization steps on both the MIT/BIH arrhythmia database and the whole dataset of our signals under different activity levels (IMEC dataset).

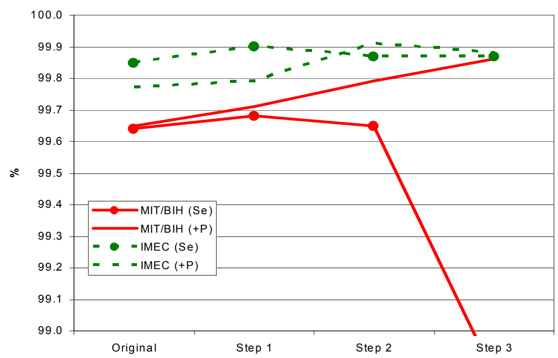

Fig. 5. Optimization Results on MIT/BIH database and our dataset.

The different changes proposed showed some improvement of the algorithm performance. In Step 1 the sensitivity and positive predictivity increased in both the MIT/BIH and our own dataset. Step 2 decreased slightly the sensitivity of the algorithm but improved significantly the positive predictivity in both datasets. Step 3 did not show much improvement on the IMEC database, but the sensitivity dropped drastically on arrhythmic ECGs (as in the MIT/BIH database), which is explained by the assumption of some regularity in the heart rate by this step.

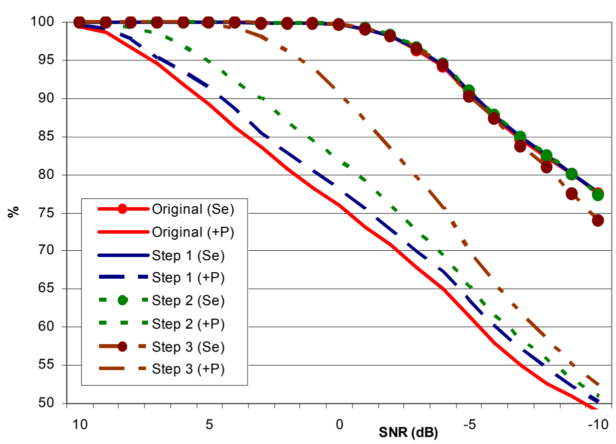

Fig. 6. Optimization Results on Noise Test.

Fig. 6 shows the results of the noise test for the different versions of the algorithm. It can be seen that while the sensitivity of the algorithm does not have a big change, the positive predictivity improves on each of the additional steps.

IV. Conclusion

This study investigates the problem of beat detection in ambulatory ECGs, emphasizing the challenge of a generic method that can be used in clinical conditions and is robust against noise. We compared three classical methods, based on Time (TD) and Wavelet Domain (DWT and CWT). A test protocol was proposed with the aim of evaluating these techniques under a wide range of conditions.

Although there is no single technique that gave the best results for all different conditions we tested, we observed that CWT had an overall superior performance to the other two on this test protocol. Therefore CWT was selected for further optimization. After the proposed changes, we got an optimal performance after Step 2. Step 3 gave significant improvement of +P at the expense of a significant decrease in Se and was therefore omitted. After optimization (up to Step 2), we obtained an improvement on +P of 0.14 in both MIT/BIH and IMEC databases, while keeping the Se on the same level. The final algorithm is very suitable for cardiac monitoring in ambulatory environments.

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