NEW METHOD FOR QRS DETECTION BASED ON THE MULTISCALE PRODUCT

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Abstract— This paper proposes a performant method for QRS detection. It is based on the analysis of ECG by the multiscale product (MP) with continuous wavelet. The multiscale product The modulus maxima detection is carried by two parameters: the period and the amplitude of the signal. This process constitutes the originality of the method and makes it more robust. After eliminating the redundant peaks, we evaluated the algorithm on the MIBIH database and achieved provide high accuracy.

Index Terms—ECG, Multiscale Product, QRS detection, Wavelet.

I. INTRODUCTION

Heart diseases are reported to have a major share in human death all over the world. Early screening and medical treatment of heart diseases can prevent sudden death of the patient
The analysis of the electro cardiogram signal has been known as a reliable technique for cardiac monitoring and disease diagnosis[1].
The R wave in the ECG result from the passage of the electrical stimulus through the main portion of the ventricular walls and is by far the biggest wave generated during normal conduction. Being the largest peaks in the ECG signal, the R wave constitute the most noticeable singularity of the signal, so detecting them returns to find the heartbeat.
Accurate determination of the R wave, in general, accurate detection of the QRS complex, is essential in computer-based ECG analysis. However, this is often a tricky task. Since Noise contamination, due to baseline drifts changes, muscular noise and motion artifacts, is frequently encountered[2]. In addition, morphological variation in the ECG waveform increase the complexity of QRS detection, due to the heterogeneity in the QRS waveform and the difficulty in differentiating the QRS complex from noise or tall peaked P and T waves [3].

Indeed, Algorithm design for QRS detection has been a topic of research for the past four decades and several techniques has been propose like digital filters[4], neural networks[5], the approaches based on signal derivative[6], adaptive methods[7], Hilbert transform[8] and wavelet transform[9][10][11].
The most promising group of algorithms is based on the wavelet transform which has emerged over recent years as the most favored tools by researchers for no-stationary signal analyzing. Since it provides high detection quality at low computational complexity[12].
Generally, it consists in finding the modulus maxima larger than a threshold obtained with a preprocessing of some initial beats like the study of.
In this work, a new method for QRS detection is proposed. It is based on the multiscale product of the wavelet transform and the modulus maxima detection by the period of the signal combined with a thresholding process. A post-processing allow redundant peaks elimination.
This paper is organized as following: In the first section an introduction to the wavelet transforms, the multiscale product and the principle of singularities detection proposed by Mallat[13].
The methodology is exposed in the second section followed by the evaluation and the discussion of the obtained results. Finally, we give the conclusion.

II. WAVELET TRANSFORM

The wavelet transform is used to decompose the signal in a set of a time-frequency atom family called wavelets. A wavelet is the mathematical function $\psi \in$ L2 (R) centered in zero, which has a mean equal to 0 and a norm equal to 1.
The function describing the wavelet is written according to a scaling factor "s" and a shift parameter "u" enabling to modify the wavelet and to define a family of functions by dilating or translating the mother wavelet defined as:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \quad (1)$$

The Continuous Wavelet Transform of a signal x(t) is defined as :

$$W\,x(u,s) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{s}}\psi^{*}\left(\frac{t-u}{s}\right)dt \quad (2)$$

In this equation, "s" is the scaling factor and "u" is the translation parameter. The "s" parameter acts as the inverse of the frequency: the more s is small the more the wavelet's support is reduced, so the central frequency of the spectrum will be higher.

III. SINGULARITIES DETECTION

The wavelet transform allows a time-frequency location of abrupt transitions and irregular pattern in the signal. Indeed, Mallat[14] proves that the singularities of the signal correspond to the points where the modulus maxima of the wavelet coefficients converge at fine scales :

$$\frac{\partial Wx(u,s)}{\partial u} = 0 \qquad (3)$$

Hence, wavelet vanishing moments characterize the type of singularity. In this case, if the wavelet has only one vanishing moment, modulus maxima are the maxima of the first derivative of a smoothed function corresponding to discontinuities of the signal. While for a wavelet with two vanishing moments, the modulus maxima correspond to discontinuities on signal derivative.

IV. THE MULTISCALE PRODUCT

The multi-scale product is a process that remarkably allows to enhance the singularities in the signal and significantly reduce the noise It is based on local maxima detection of the wavelet coefficients But instead of having a single wavelet transform we perform a non-linear combination of several wavelet transform at some adjacent scales. The multiscale product is used to take advantage of several scales values accentuating the singularities of the signal and facilitating their detection[15].

A multiscale analysis of a function x(n) is described by:

$$p(t) = \prod_{i=1}^{n} Wx(u, s_i) \qquad (4)$$

Where n is the number of the scales and $W_{x(u,si)}$ is the wavelet transform of x at the scale s_i.

Facing the dilemma of the choice of the scale between the very large scales which will strongly smooth the signal and the small scale which will accentuate the details, it is difficult to find the optimal scale with a single wavelet, the multiscale product is then the solution.

V. METHODOLOGY

The proposed method contain mainly three stages: in the first step, the multiscale product of the signal is computed, then the detection of the modulus maxima is performed. The detection process is carried by two parameters the period of the signal and its amplitude. This stage is, therefore composed of two techniques: peaks localization by the period of the signal combined with a thresholding technique. The final step tends to eliminate the redundant peaks to finally obtain the QRS positions.

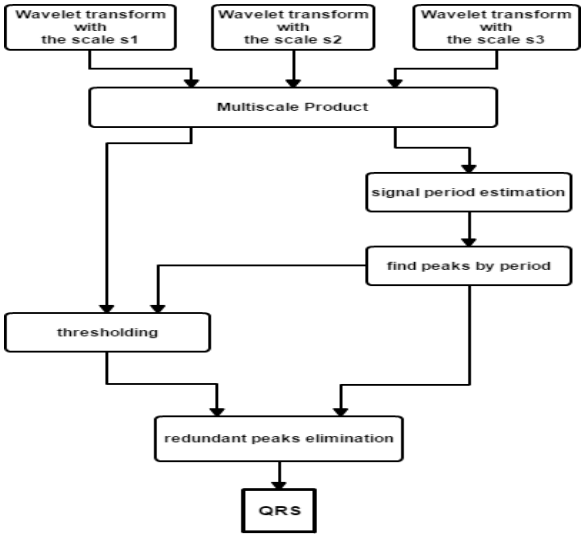


Fig 1: **organigram of the method**

A. Signal analysis by the Multiscale product

In this stage, three wavelet transforms are performed with three different scales: s1=2, s2=3 and s3=5. We choose the second derivative of the Gaussian commonly known as Mexican hat. This wavelet has been widely used for the detection of QRS due to the similarity between its waveform and the shape of the QRS complex.

The wavelet is described with the following equation:

$$\psi(t) = \frac{2}{\pi^{1/4}\sqrt{3\sigma}}\left(\frac{t^2}{\sigma^2} - 1\right)\exp\left(\frac{-t^2}{2\sigma^2}\right) \qquad (5)$$

Fig.2 shows an ECG signal followed by its wavelet transform with the three used scales. We can see how much the MP can smooth the signal and suppress the noise the noise comparatively with a single wavelet transform. The singularity are therefore enhanced and highlighted.

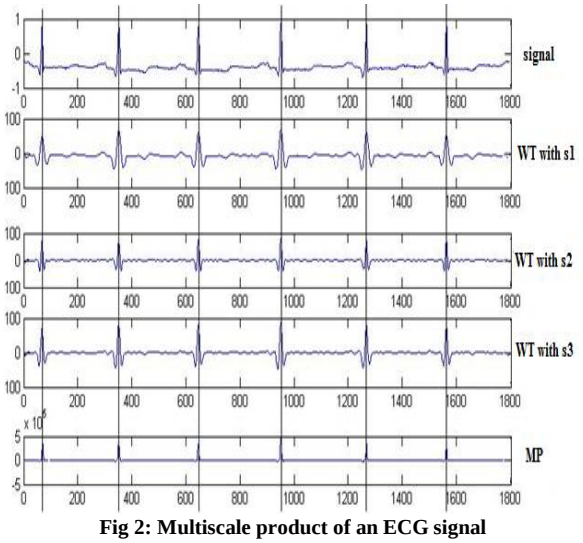


Fig 2: Multiscale product of an ECG signal

B. Signal Period estimation

The period of the signal is estimated via the autocorrelation of the Multiscale product of the signal.

Indeed, the autocorrelation is a symmetric function allowing to find repeating patterns such as the presence of a periodic pattern obscured by noise.
The autocorrelation of a periodic signal is a periodic function. Its period is equal to the average period of the signal. Since the first peak of this function has an abscissa equal to zero, finding the second peak give us an estimation of the average period of the signal.
Fig.3 show an ECG signal followed his MP and the autocorrelation function.

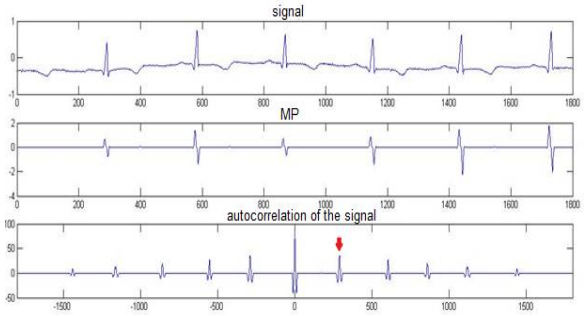


Fig 3: autocorrelation of the signal

C. Maxima detection by period

The modulus maxima are detected by the period of the signal previously estimated. In each period of the signal, the peak with the highest amplitude is retained. We obtain a list of peaks spaced by the average period of the signal but in case of localized arrhythmia some QRS might be wrongly dismissed. The detection process is, therefore completed by a thresholding to identify the missed peaks.

D. Thresholding

A thresholding process is established to find the most important singularities of the signal which might belong to R-waves. The threshold TH is computed by the amplitude of the peaks localized in the previous stage:

$$TH = 0.25 * \frac{\sum_{i=1}^{n_3} MP(x(mx_i))}{n} \quad (6)$$

Where $mx_1 \ldots mx_n$ are the QRS found by the period of the signal.

E. Post-processing

In this stage, the two lists of maxima obtained from the two previous steps are merged and a verification is done to eliminate the redundant peaks. An interval threshold is empirically defined as 0.2 secondes. If the distance between two peaks is less than the threshold then the peak with the lower amplitude is deleted.

VI. RESULTS AND INTERPRETATION

The proposed algorithm was tested on real signals from the MIT-BIH Arrythmia database. This database contains 48 multichannel recordings each with 30-min duration and a sampling frequency of 360 HZ. For each record there are reference annotations indicating the QRS positions and allowing to evaluate the performance of QRS detection algorithm[16].

We evaluated the results obtained using two parameters: the accuracy ACC and the sensitivity Se.

$$Acc = \frac{TP}{TP + FN + FP} \quad (7)$$

$$Se = \frac{TP}{TP + FN} \quad (8)$$

Where
TP: the number of the true positive
FN: the number of false negative
FP: the number of false positive

Signal	QRS	TP	FN	F	ACC	SE %
100	2273	2273	0	0	100	100
101	1865	1861	4	0	99,79	99,79
102	2187	2181	6	0	99,73	99,73
103	2084	2084	0	0	100	100
104	2230	2221	9	0	99,60	99,60
105	2575	2560	15	18	98,73	99,42
106	2030	2025	5	0	99,75	99,75
107	2137	2118	19	0	99,11	99,11
108	1765	1749	16	1	99,04	99,09
109	2532	2527	5	0	99,80	99,80
111	2124	2121	3	0	99,86	99,86
112	2539	2539	0	1	99,96	100
114	1880	1863	17	0	99,10	99,10
113	1795	1794	1	0	99,94	99,94
115	1955	1953	2	0	99,90	99,90
116	2412	2394	18	0	99,25	99,25
117	1534	1534	0	1	99,93	100
118	2278	2278	0	0	100	100
119	1987	1985	2	0	99,90	99,90
121	1863	1862	1	1	99,89	99,95
122	2479	2476	3	0	99,88	99,88
123	1519	1515	4	0	99,74	99,74
124	1619	1618	1	2	99,81	99,94
200	2601	2601	0	1	99,96	100
201	1963	1959	4	0	99,80	99,80
202	2136	2130	6	0	99,72	99,72
203	2980	2942	38	4	98,59	98,72
205	2656	2654	2	0	99,92	99,92
207	1862	1841	21	5	98,61	98,87
208	2955	2926	29	3	98,92	99,02
209	3005	3005	0	1	99,97	100
210	2650	2650	0	0	100	100
212	2748	2748	0	0	100	100
213	3251	3234	17	0	99,48	99,48
214	2254	2253	1	2	99,87	99,96
215	3363	3361	2	0	99,94	99,94
217	2208	2207	1	4	99,77	99,95
219	2154	2152	2	0	99,91	99,91
220	2048	2048	0	9	99,56	100
221	2427	2425	2	0	99,92	99,92

222	2483	2468	15	0	99,40	99,40
223	2605	2602	3	4	99,73	99,88
228	2053	2053	0	4	99,81	100
230	2256	2256	0	4	99,82	100
231	1571	1571	0	1	99,94	100
232	1780	1777	3	3	99,66	99,83
233	3079	3073	6	0	99,81	99,81
234	2753	2750	3	0	99,89	99,89
Total	**109503**	**109217**	**286**	**69**	**99,68**	**99,74**

Table 1: QRS detection results on the MITBIH database

Table I presents the results for all the signals from the MIT-BIH database. The method produced 99.68% of total accuracy and 99.74% of sensitivity. From 109503 QRS to detect, 109217 were correctly localized, 286 peaks were missed and 96 false positives were observed.

The algorithm achieved an accuracy of 100% on regular ECG like the signals N° 100, N°103 and N° 118.

The ECG N° 107 include paced beats and peaked T waves. 2118 QRS were correctly identified in this signal. The accuracy and the sensitivity are both about of 99.11%.

Fig.4 shows an example of 10 seconds from the signal N° 107. The signal is shown in first followed by its MP and the reference annotations. We can notice the amplitude of the T waves remarkably high. The circles indicate the positions of the detected R waves. All the QRS in this example have been correctly detected despite the abnormality of the signal.

The signal N° 108 exhibits considerable noise and a significant number of QRS complex with abnormal shape. This signal is commonly known for being difficult to handle.

Our method achieved an accuracy of 99,04% and a sensitivity of 99,08%. Knowing that some methods go so far as to eliminate this signal due to its complexity, those rates are considered as satisfactory.

Fig.5 shows a portion of 10 seconds from the signal N°108. We can notice the particular shape of the 10 QRS complex in the signal. There were all correctly detected by the proposed method.

The greatest number of false detections is noticed on the signals N° 208, N°207 and N°203, which are extremely noisy.

Indeed the signal N°203 presents the lowest accuracy rate, it is about 98,59% and the sensitivity is of 98,72% . This signal contains multiform PVC, strong localized arrhythmia and a significant noise.

Fig.6 shows the detection's results on a portion from the signal N°203. 15 QRS were correctly detected but we can notice 6 false negatives due to localized deformity and the very low amplitude of some QRS. In this case, we can see that the MP does not contains peaks on the abscissa of such QRS.

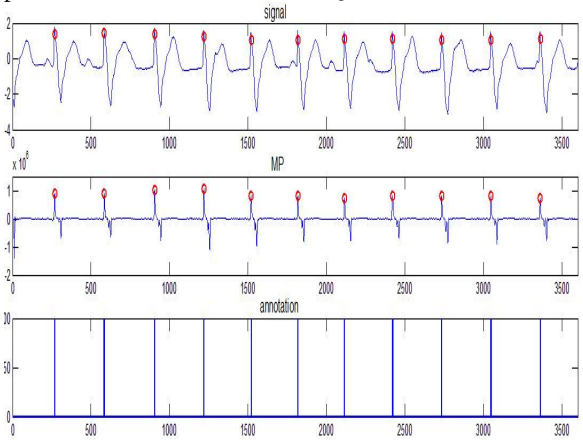


Fig 4: The QRS detection on the signal n°107

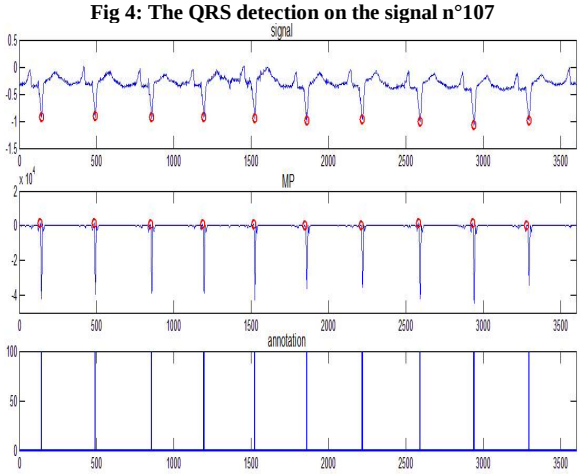


Fig 5: The QRS detection on the signal n°107

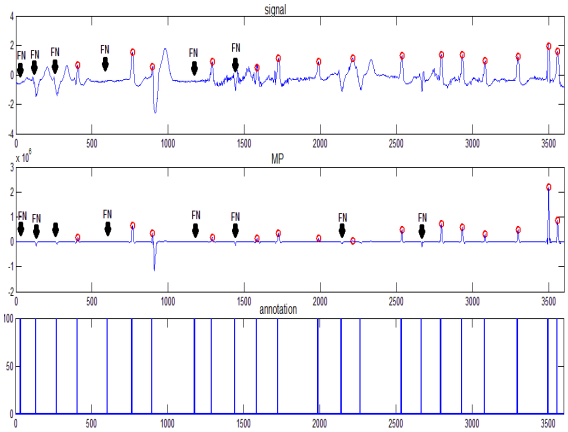


Fig 6: The QRS detection on the signal n°203

Table 2 summarizes results of 10 methods of QRS detection in the literature. All of them are using the MITBIH database. The methods range from the oldest to the most recent and are based on several techniques. Some methods used all the datasets of the database but some other had chosen to do the validation on only some signals.

Our method achieved one of the best accuracy comparatively with all this methods. Only sahambi had reached a better accuracy but the tests were done

for only 14481 beats while our method had detected is validated for 109503 QRS complex.

Method	#total	FN	FP	ACC	SE%
Tompkins [17]	116137	507	277	99,33	99,56
Sahambi [18]	14481	93	84	98,78	99,36
Benitez [19]	-	-	-	99.64	99.81
Chen[20]	102654	459	529	99,04	99,55
Ghaffari [21]	110159	120	322	99,60	99,89
Sasikala [22]	2354	6	6	99.49	99.74
Zidelmal [23]	109494	393	193	99,47	99,64
Bouaziz [24]	109586	140	232	99,66	99,87
Deepu [25]	109508	395	201	99.45	99.64
Rodriguez [26]	44715	58	137	99,57	99,87
This method	**109503**	**188**	**56**	**99,68**	**99,74**

Table 2: Comparison with existing methods

CONCLUSION

An automatic method for QRS localization has been proposed. It is based on the Multiscale Product of the continuous wavelet transform coefficients and the modulus maxima detection. We have shown how much the multiscale product can smooth the signal and enhance the singularities allowing their detection. The originality of the approach lies in the modulus maxima detection method. It is carried by two parameters the period and the amplitude of the signal. This process makes the method more robust and efficient.

The proposed algorithm has been validated on all the signals of the MITBIH database. Our method achieved very good detection performance. The total accuracy is about 99,68% and the sensitivity is of 99.74%.

The accuracy and the sensitivity reach 100% for five records that contains clear R-peaks and few artifacts. Those rates falls slightly for signals extremely noisy and deformed but still good enough. The minimal accuracy rate is about 98,59% and sensitivity rate is not less than 98.72%.

The method is fast simple, does not need learning period and proves to be efficient even on noisy and irregular signal. Nevertheless, we can consider improving the result by trying to use other wavelet function.

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