Improvement of the Detection of the QRS Complex, T and P Waves in an Electrocardiogram Signal using 12 Leads versus 2 Leads

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Abstract: The electrical field potential of the heart recorded from the thoracic part of the human body is depicted by the electrocardiogram signal. This last one is complex and depends on many factors: Position of heart, thickness of the body skin, surface electrode conductivity, acquisition noise and many others. In clinical use, the ECG signal is analysed using twelve leads but in many works in the literature, the analysis methods of the ECG is based on two leads. We present a new method to delineate QRS complexes and T and P waves from electrocardiogram signal. It is based on the continuous wavelet transform. The method is applied on several leads, recorded simultaneously, to improve the localization of the detection. Indeed, if a delineation method is applied on only one lead with some disturbances in it, the result of the delineation could be affected. As the method proposed here merges the result of several leads, the delineation is less affected by disturbances on few leads. The results from this method and from a doctor in medicine are compared. That shows the good ability to separate waves and the enhancement of delineation accuracy when several leads are used.

1 INTRODUCTION

The QRS, P and T waves detection in the electrocardiogram (ECG) represents a great interest to diagnose pathological conditions (Navoret et al., 2013; Mahamat et al., 2016a; Mahamat et al., 2016b). However, their extraction from ECG is not an easy task. Some methods exist, including mathematical models (Madeiro et al., 2013), peak detection (Zhu and Dong, 2013), nonlinear transforms (Sun and Suppappola, 1994), filtering (Bashir et al., 2014). The shapes of QRS, P and T waves are well known, especially their time and frequency components which depend on the physiological characteristics of people. It may be difficult to extract ECG complexes because their frequency compositions are close to some noises. The algorithm presented here uses the continuous wavelet transform (CWT) which keeps a good frequency resolution. Wavelet transforms (Addison, 2005; Li et al., 1995; Zidelmal et al., 2012) have already been applied to ECG signals to enhance QRS detection, to delineate the ECG feature, and to reduce computation time. However, the major part of ECG delineation methods deals with Discret Wavelet Transform, which loses frequency resolution due to re-sampling at each decomposition. That is not the case in CWT. The method was tested with The Computers in Cardiology Challenge 2011 database because it contains 12 leads for each ECG. From this collection, a set of fifty 12 leads ECGs, chosen in the "acceptable records" list given by Physionet, was used for our tests. In addition, this database provides ECG from patients with different pathologies leading to some irregularities in ECGs. Therefore, our algorithm (Yochum et al., 2016) was tested on several particular ECGs such as arrhythmias and extrasystoles. Our method uses the 12 leads together to extract QRS, P and T waves from each ECG, which improve the localization. The method performs a serial detection of the components of the ECG signal as these components usually follow a decrease in their energy (QRS complexes contain more energy than T wave, and T waves contain more energy than P waves). Results show the use of 12 leads simultaneously reinforces the detection and also avoids misdetections if disturbances exist on few leads.

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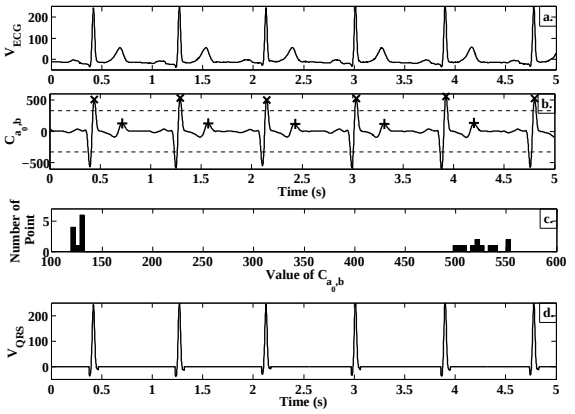

Figure 1: a. Example of V_{ECG} signal from Physionet collection. b. CWT transformation of V_{ECG} signal with $a_0 = 38$ corresponding to the maximum of $C_{a,b}$ coefficient. We can also see the representation of the difference between maxima of $C_{a_0,b}$ coefficients during QRS complexes (cross) and maxima $C_{a_0,b}$ coefficients during T complexes (plus) which allows the localization of QRS complexes. Both dashed lines are the h threshold representation of positive and negative parts computed with the equation 2. c. Histogram of local maxima values. We distinguish a bimodal distribution. d. V_{QRS} result example with m_{QRS} mask applied on the V_{ECG} signal in a. A good localization of QRS complexes are observed.

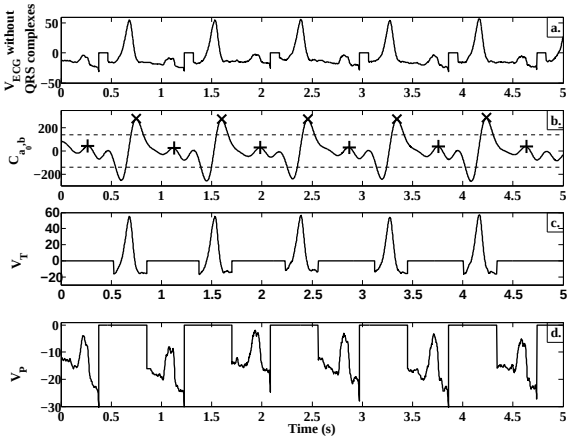

Figure 2: a) V_{ECG} signal without QRS complexes corresponding to the examples in Figures 1. b) $C_{a_0,b}$ coefficients from CWT with a_0 scale factor. Both dashed lines are the h threshold representation for positive and negative parts computed from the equation 2. c.V_T result example. d.V_P example. A good localization of T and P waves is observed.

2 METHOD

The algorithm is remained in this part, but all the details can be found in (Yochum et al., 2016). It proceeds in four steps. The first step determines the best scale factor which exists between the ECG signal (V_{ECG}) and a mother wavelet (ψ the Daubechie wavelet) according to a set of scale factors. A CWT is applied between V_{ECG} and ψ on a discrete grid of scale factors a and a position b on the time axis. Such as:

$$C_{a,b}(V_{ECG}(t),\psi(t)) = \int_{-\infty}^{\infty} V_{ECG}(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt, \quad (1)$$

Scale factors go from 1 to 100 by step of 1. This range allows the analysis of various sizes of ECG complex. To find the best scale factor a_0, we estimate the scale factor which corresponds to the maximal value of the CWT coefficients, named $C_{a,b}$. The second step builds a temporal mask in the wavelet domain by using the $C_{a_0,b}$ coefficient which is a vector. This mask allows the extraction of QRS complexes from the ECG signal. Figure 1b shows an example of a CWT applied on a V_{ECG} (see panel a in Figure 1). Notice that $C_{a_0,b}$ values corresponding to QRS complexes are higher than $C_{a_0,b}$ values corresponding to T or P waves, which is not always the case in V_{ECG}. Using this fact, QRS complexes is distinguished from V_{ECG} with a thresholding method. A threshold is created automatically using a local maxima method. Those maxima are represented in Figure 1b, by crosses (during QRS) and plus (during T). In Figure 1c, the histogram of those maxima is plotted. It shows a bimodal distribution. To find automatically the threshold, the centroid of these points in the histogram is computed:

$$h = \frac{\sum_{i=1}^{n} x_i y_i}{\sum_{i=1}^{n} y_i}, \quad (2)$$

where h is the threshold, x_i are the local maxima $C_{a_0,b}$ values, y_i are the distribution value of $C_{a_0,b}$ coefficients and n represents the histogram range. Then, once the threshold is computed, a mask is created using $|C_{a_0,b}|$ absolute coefficient values and the threshold h. A preliminary mask (m_p) is equal to 1 if $|C_{a_0,b}|$ are above the threshold, which corresponds to the QRS complexes. The mask is equal to 0 if $|C_{a_0,b}|$ are below the threshold, corresponding to the T or P wave parts. To avoid some glitches in the mask, an erosion algorithm (a mathematical morphology operation (Serra, 1982)) is applied to the m_p and gives the final mask named m_{QRS}. The third step localizes QRS complexes by multiplying the mask m_{QRS} with the V_{ECG} signal.

$$V_{QRS}(t) = V_{ECG}(t) \cdot m_{QRS}(t), \quad (3)$$

An example of V_{QRS} is shown in Figure 1d which corresponds to V_{ECG} signal in Figure 1a. As we can see, QRS complexes are well localized in V_{ECG} signal. The last step of the method is to repeat the three first steps on the V_{ECG} signal without QRS complexes. An example is shown in Figure 2a. In Figure 2b, we see $C_{a_0,b}$ coefficients corresponding to the CWT of the

V_{ECG} signal without QRS complexes. The local maxima are represented by crosses (during T waves) and plus (during P waves). Thanks to those local maxima, the threshold was computed. It is plotted with the dashed line. Then, the mask m_T is created to find T waves signal V_T with:

$$V_T(t) = V_{ECG}(t) \cdot m_T(t) \quad (4)$$

An example of V_T is shown in Figure 2c which corresponds to the V_{ECG} signal in Figure 1a. As we can see, T waves are well localized from V_{ECG} signal. The P waves are detected as the rest of the V_{ECG} signal without QRS complexes and T waves. In addition, the smallest remaining segments are removed. An example is displayed in Figure 2d.

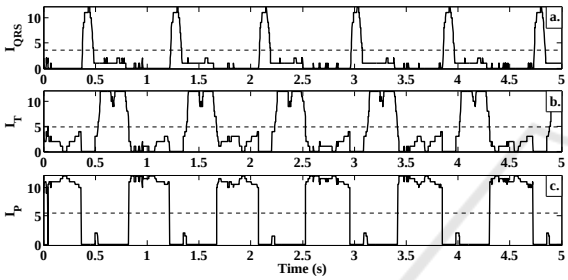

Figure 3: Examples of results of reliability indexes in a) for the QRS complexes, in b) for the T complexes and in c) for the P complexes. The threshold is plotted with dashed lines for each complex as the mean of the reliability index.

To improve the localization of each complex QRS, T and P in an ECG, the results of several leads were combined. In cardiac diagnostic test, it is common to have several leads in ECG signal. In this case, even if few leads are unusable, merging results of each lead could increase the localization of each complex or wave. Masks m_{QRS_k}, m_{T_k} and m_{P_k} created for each lead (where k = [1,12], $k \in \mathbb{N}$ according to the lead) are then used to compute a reliability index. If the localization result is common to the twelve leads, then there is a strong probability that the QRS complexes or P and T waves are well detected. On the other hand, if there are only few localizations among the twelve leads, then there is a low probability that the localization result is true. A reliability index of each QRS complex or P and T wave is then computed as the sum of twelve lead masks:

$$I_w(t) = \sum_{k=1}^{12} m_{h_k}(t) \quad (5)$$

where w is QRS, T or P. Therefore, the reliability indexes are respectively I_{QRS} for QRS complexes, I_T for T waves and I_P for P waves. A good localization is more likely if the index is close to 12. In the opposite case, a good localization is unlikely if the index is

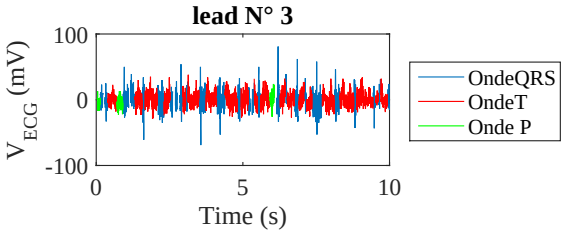

Figure 4: Application of the algorithm on 1 lead very noisy ECG signal. Note that the detection is not correct.

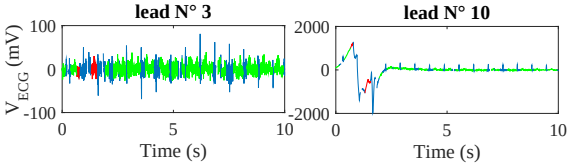

Figure 5: Application of the algorithm on 2 leads, a very noisy one and a disturbed one. Note that the detection is not correct. The colors correspond to the legend in Figure 4.

close to 0. In Figure 3, a result of reliability indexes is shown (in a for the QRS, in b for the T and in c for the P). An automatic threshold is computed for each wave as the mean of reliability index. In Figure 3, these three thresholds are plotted with dashed lines. The localization of a complex is considered true if the value of the reliability index is above the threshold otherwise it is considered false.

To illustrate the advantage of using more than one lead, Figures 4 to 7 present the result of the method with 1, 2, 4 and 12 leads. In Figure 4 just one noisy lead is used. Note that the detection is incorrect. In Figure 5 only two leads are used, a noisy one and a disturbed one. Note, once again, that the detection is incorrect. In Figure 6 only four leads are used with a noisy one and a disturbed one. Note that, this time, the detection is visually correct, even if two leads are perturbed. Because the algorithm used multi-lead instead of just one, the algorithm is able to compensate disturbances on several leads. The same fact is shown in Figure 7.

3 RESULTS

In Figure 8, four different examples are given showing some particular cases where the determination of QRS complex, T and P waves might be difficult. In panel a, the SNR ratio of the ECG is really low. Nevertheless, the different waves are well detected by the algorithm without any post acquisition process (denoising, amplitude enhancement,...). In panel b, T waves are higher than QRS waves. That could lead to mix up of those two if a thresholding technique

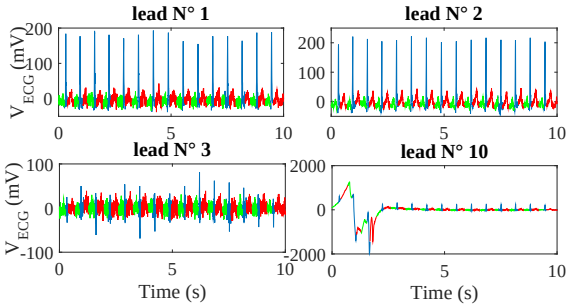

Figure 6: Application of the algorithm on 4 leads with a very noisy one and a disturbed one. Note that the detection is visually correct even if two leads are very perturbed. The colors correspond to the legend in Figure 4.

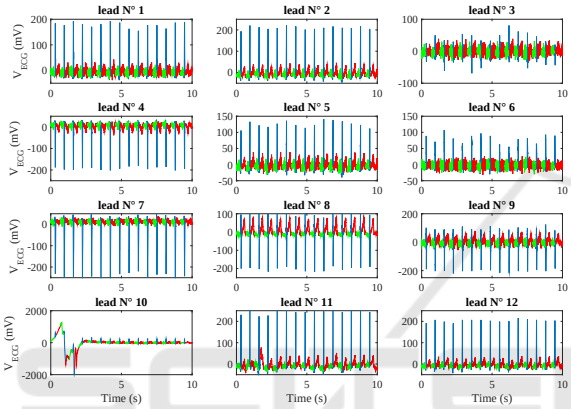

Figure 7: Application of the algorithm on 12 leads with a very noisy one and a disturbed one. Note that the detection is visually correct even if two leads are very perturbed. Colors correspond to the legend in Figure 4.

was used directly on the ECG signal. However, as the thresholding is done in the wavelet domain, the result shows a correct complexe detection. It is possible that the baseline of an ECG is not stable. This is the case in panel c. Despite that, the algorithm shares correctly each wave without low frequency filtering. In panel d, we can see that all waves are in the same range of amplitude which could lead to mix them. However, the robustness of our algorithm prevents this and the results are therefore not affected. In this case, standard thresholding algorithms are unable to discriminate correctly QRS complexes and T waves, they could be mixed.

4 APPLICABILITY

The results of our algorithm applied to the Physionet collection is compared with delineation determined by a doctor in medicine. The interest is to know the beginning and the end for each ECG complexes from an expert as a true result. The physician chooses one

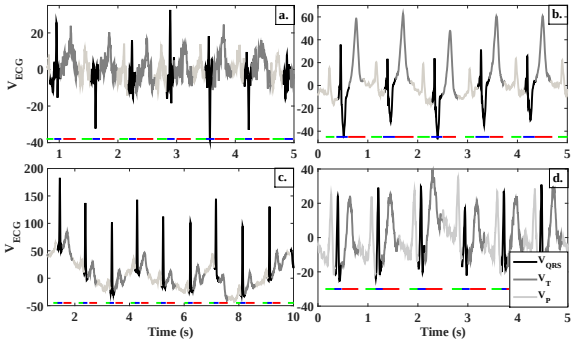

Figure 8: Example of results with some cases where the ECG complexes are usually difficult to distinguish. a) the ECG has got a law SNR ratio. We see that the algorithm is able to discriminate each wave without filtering. b) the T waves are higher than the QRS waves. These two waves could be mix up if we use a thresholding technique directly on the ECG signal. However, in our case the thresholding is done in the wavelet domain. c) The baseline of the ECG is not stable. Despite that, the algorithm share correctly each wave. d) All waves are in the same range of amplitude and the results are not affected. QRS (black lines), T (dark gray lines) and P (pale gray lines).

lead from the twelve leads and determines for each QRS complex, P and T wave of this lead the beginning and the end times. These data are then used as correct result of ECG delineation. From the algorithm and the physician, two results by ECG are obtained: the real moments of QRS, T and P in the ECG tagged by the doctor, and the results given by the algorithm. Thanks to our algorithm and the physician, two results for 12 ECG leads are obtained: the real moments $D_w(n)$ of QRS, T and P in the ECG tagged by the physician and the results $A_w(n)$ given by our algorithm. $A_w(n)$ and $D_w(n)$ are equal to 1 if the QRS, T or P wave is detected and 0 (noted $\overline{A_w(n)}$ and $\overline{D_w(n)}$) if is not, they are therefore logical vectors. For each $A_w(n)$ and $D_w(n)$ pair, the coverage rate Se_w is computed (w denotes QRS, T and P waves.). This coverage is determined as a logical AND between $A_w(n)$ and $D_w(n)$ divided by $D_w(n)$ as shown in the eq.(10). The coverage gives the common result between the algorithm and the physician determination. This coverage is well known as the sensitivity which is computed thanks to TP (True Positive), TN (True Negative), FP (False Positive) and FN (False Negative) where

$$TP_w = \sum_{n=0}^{N} A_w(n) \cdot D_w(n), \tag{6}$$

$$TN_w = \sum_{n=0}^{N} \overline{A_w(n)} \cdot \overline{D_w(n)}, \tag{7}$$

$$FP_w = \sum_{n=0}^{N} A_w(n) \cdot \overline{D_w(n)}, \tag{8}$$

$$FN_w = \sum_{n=0}^{N} \overline{A_w(n)} \cdot D_w(n). \quad (9)$$

Those values are then scalars. Therefore, the sensitivity Se_w is computed as:

$$Se_w = \frac{TP_w}{TP_w + FN_w}. \quad (10)$$

Se_w shows the ability of our algorithm to give the same results as the physician. For each ECG, the specificity has been determined.

$$Sp_w = \frac{TN_w}{TN_w + FP_w}. \quad (11)$$

From the equations (6) to (11), the Youden Y_w and the accuracy Acc_w indexes can be defined:

$$Y_w = Se_w + Sp_w - 1, \quad (12)$$

$$Acc_w = \frac{TP_w + TN_w}{TP_w + TN_w + FP_w + FN_w}. \quad (13)$$

The reliability indexes introduced above, have been calculated on the results of the fifty ECG samples and their mean values are given in Table 1. These indexes show a good ability of the algorithm to localize ECG complexes since indexes are close to one. The specificity for T and P complexes are a little bit lower because our algorithm detects a larger area than the doctor which induces higher TN values. Our algorithm is able to well determine the duration of the QRS complexes in the ECGs. However, the durations for the T and P waves are longer than for the doctor delineation. Nevertheless, the coverage shows that our algorithm contains the entire parts determined by the doctor. Therefore, some other treatments could be done to improve the localization of T and P complexes or to find other characteristics such as amplitudes and interspike durations for instance.

Table 1: Mean values of sensitivity, specificity, Youden index and accuracy from the fifty ECG samples.

Waves	$Se(\%)$	$Sp(\%)$	$Y(\%)$	$Acc(\%)$
QRS	99.87	98.42	98.29	98.64
T	99.17	93.21	91.38	94.83
P	99.06	91.21	90.27	92.44

In addition, to better quantify the quality of the results, Table 2 presents the sensitivity index for the use of different number of leads. As we can see, the algorithm gives better results if a high number of leads is used. It is particularly the case for the P wave.

Table 2: Improvement of wave detection with the increase of leads.

Leads/Wave	QRS	T	P
1	0.9134	0.3420	0.1643
2	0.9059	0.5103	0.5371
3	0.9752	0.7082	0.6396
4	0.9851	0.9939	0.9611
5	0.9802	0.9963	0.9717
6	0.9752	0.9988	0.9806
7	0.9802	1	0.9788
8	0.9823	1	0.9851
9	0.9876	1	0.9851
10	0.9912	1	0.9851
11	0.9929	1	0.9851
12	0.9951	1	0.9912

5 CONCLUSIONS

The algorithm proposed here to delineate QRS, T and P waves in ECG signal uses a wavelet domain transform with CWT. It can simultaneously detect the QRS, T and P patterns on each ECG lead. A thresholding method separates the complexes in the wavelet domain instead of in the temporal domain. Indeed, the amplitudes among waves are more different in wavelet domain than in the temporal domain, which helps the detection. To improve QRS, T and P wave localizations in ECG signal, results from several leads are combined with a fusion method. A comparison with doctor tags thanks to sensitivity, specificity, Youden and accuracy indexes shows the efficiency of this method. In addition, the utility of using several leads instead of only one has been proven, in particular when some leads are disturbed. We plan to improve this method by detecting also fiducial markers which are useful for pathologic diagnosis. This method could be implemented in a hardware setup in order to help physicians and to facilitate the ECG analysis.

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