Detection of Sharp Wave Activity in Biological Signals using Differentiation between Consecutive Samples

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Abstract: A number of signal processing techniques make use of first-derivative-based approaches for detecting regions of interest in biological signals. For instance, central and five-point derivative-based algorithms are employed for emphasizing and identification of the QRS complex in the ECG signal. Signal differentiation approaches are also used for detection and removal of high-frequency components associated to artefacts in the EEG signal. This paper aims to present a first-derivative approach based upon differentiation of consecutive samples – signal slope adaption (SSD) – for detecting regions of sharp wave activity in biological signals. A case study is analysed whereby SSD is used to mark and select the sharp wave activity associated to the QRS complex in the electrocardiogram. Evaluation of our methodology reveals that SSD shows to be effective for identification of QRS samples and, thereby, could be also employed to detect samples associated to sharp wave activity regions of other biological signals which possess similar signal slope behaviour.

1 INTRODUCTION

In research and clinical practice, automatic measurement and recognition of parameters in biological signals are fundamental to implement computer-based tools for data analysis and patient monitoring. In this context, detection of sharp wave activity or instantaneous signal variability represents a useful parameter in digital biological signal processing. A classical example of identification of a region with steep wave activity in biological signals is the detection of the QRS complex for measurement of the heart rate variability (HRV), which constitutes an important method for assessment of the cardiac regulation and diagnostic of disorders such as arrhythmias and congestive heart failure (Clifford, 2006); (Rangayyan, 2002).

A number of methodologies which make use of first-derivative-based approaches and differentiation of the ECG signal are proposed in the literature for QRS detection (Pan and Tompkins, 1985); (Hamilton and Tompkins, 1986); (Benitez et al., 2000); (Köhler et al., 2002); (Rezk et al. 2011). The basic idea of differentiating the digital signal is that such a feature can be used for characterizing and emphasizing regions of the signal which contain sharp wave activity or specific slope features, as is the case of the QRS complex (Köhler et al., 2002). As mentioned by Rangayyan (2002), the QRS complex has the largest signal slope in a cardiac cycle due to rapid conduction and depolarization characteristics of the ventricles. First-derivative approaches are reported to be robust under conditions of changes in QRS amplitude and for ECG excerpts corrupted by baseline drifts, motion artefacts, and muscular activity (Arzeno et al. 2008); (Rangayyan, 2002); (Clifford, 2006).

Another first-derivative-based approach for fast wave activity detection is associated with the identification and removal of artefacts from the EEG signal, as proposed by Van de Velde et al. (1998) and Ferreira et al. (2012). According to Van de Velde et al. (1998), a slope differentiator procedure is employed for detection of the larger signal slope related to the higher-frequency of muscles artefacts components in comparison to the EEG. By using the same idea, Ferreira et al. (2012) present an approach based upon differentiation of consecutive samples of the EEG signal for identification and removal of gradient artefacts residuals from the

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electroencephalogram recorded within the fMRI magnetic scanner. Thus, in both of the cases above, the larger slope of the artefact interference is used to identify whether or not a sample is artefact free.

First-derivative-based methods have the advantage of not requiring manual segmentation of data, training of the algorithms or patient-specific modifications. Furthermore, they are often implemented in real-time applications since they do not require extensive computations (Arzeno et al., 2008). Signal first-derivative-based approaches can be used for identifying determined frequency properties in the signal as well (Cluitmans et al., 1993); (Van de Velde et al., 1998).

2 OBJECTIVES

Allen et al. (1998) propose a methodology for ballistogram artefacts removal from the EEG signal recorded during combined EEG-fMRI which makes use of R-peaks detection in the ECG signal simultaneously registered. The ballistogram or pulse artefact is induced in the electrodes of the electroencephalograph by the pulsatile movement of blood in scalp arteries within the magnetic static field (B_0) of the magnetic scanner. According to Allen et al., the identified QRS peaks in the ECG signal are used to calculate an average pulse artefact in the EEG signal which is then subtracted from those regions where the ballistogram artefact appears. A procedure to extract the ECG peaks based upon data segmentation and training is proposed within the methodology for average pulse artefact subtraction by those authors.

During application of our method proposed in Ferreira et al. (2012) for identification and removal of residual gradient artefacts from the EEG signal, we noticed that the same approach could be modified and used for detection of the sharp wave activity associated to the ECG peaks, as well as to other types of biological signals. Thereby, it could be used during removal of the ballistogram artefact according to the methodology of Allen et al. (1998). Moreover, the advantages mentioned by Arzeno et al. (2008) by using first-derivative techniques could be incorporated to that methodology.

The objective of this paper is to propose and assess an approach for sharp wave identification in biological signals which makes use of the difference between consecutive samples of the signal, modified from Ferreira et al. (2012). In this sense, a case study is presented in which our method is applied to identify the sharp wave activity associated to the QRS complex of the ECG signal.

3 MATERIALS AND METHODS

3.1 Subjects

For application and evaluation of the proposed methodology for fast wave activity detection, we used data from the MIT-BH Arrhythmia and the MIT-BH Noise Stress Test databases (MIT-BIH, 1998). These databases consist of 30 min ambulatory ECG recordings whose sampling rating for signal acquiring was 360 samples per second.

For performance evaluation purposes, we implemented and applied a QRS detector using our methodology to the 12 recordings of the MIT-BH Noise Stress Test Database.

3.2 Differentiation between Consecutive Samples for Sharp Wave Activity Detection

Ferreira et al. (2012) describe a methodology for identification and removal of gradient artefact residuals from the EEG signal which is based upon the differentiation of consecutive samples of the digital signal. According to such an approach, the larger slope associated to the sharp wave activity of the gradient artefact residuals is used for detecting EEG samples which contain artefact interference. In order to identify which samples are in the region of fast wave activity, a slope threshold (*thrs*) is estimated in such a way that if the sample has signal slope larger than this threshold, it is then classified to belong to the sharp wave activity region. *thrs* can be estimated, for example, taking into account the probability distribution of the signal slope.

The same idea can be applied for other types of biological signal with regions of sharp wave activity. It is the case of the QRS complex whose samples have signal slope much larger than other regions of the ECG signal (Rangayyan, 2002). The signal of figure 1a consists of an excerpt of 3600 samples (10 s) of the MIT-BH Arrhythmia Database recording 103. The respective differentiated signal is shown in figure 1b. Such a differentiation was obtained by subtraction of consecutive samples of the ECG signal, *diff* (**ECG**). Clearly, it can be noticed that higher values of the differentiated ECG are coincident with the region of the QRS complex.

By analysing probability distributions of the signal slope of standard clinical ECG signals with high SNR, we could infer that the slope of samples

which belong to QRS regions are located above the threshold, *thrs*, calculated considering the average and the standard deviation of *diff* (**ECG**):

$$thrs = (\mu_{diff(\mathbf{ECG})} + \sigma_{diff(\mathbf{ECG})}), \quad (1)$$

where $\mu_{diff(\mathbf{ECG})}$ is the average and $\sigma_{diff(\mathbf{ECG})}$ is the standard deviation of *diff* (**ECG**), considering a window whose number of points is equal to the length of the differentiated ECG. It is noteworthy that the parameter *thrs* also corresponds to the RMS value of *diff* (**ECG**).

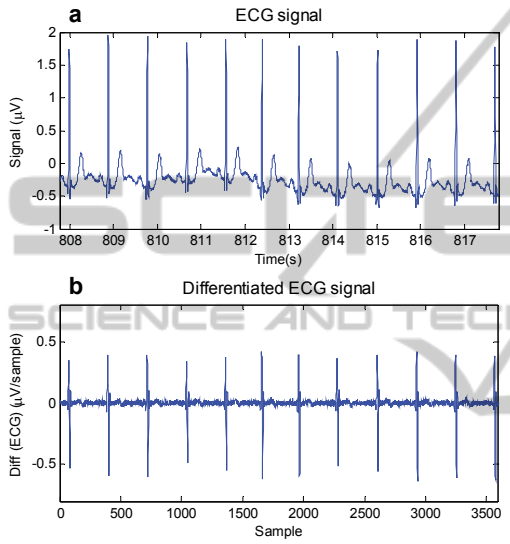

Figure 1: (a) Excerpt of 3600 samples (10 s) of the MIT-BH Arrhythmia Database recording 103 and (b) respective differentiated signal *diff* (**ECG**).

Taking into account the remarks above, a modified methodology from Ferreira et al. (2012), herein named signal slope adaption (SSD), was developed and is employed in this work in order to carry out the localization of the sharp wave activity associated to the QRS complexes, described as follows.

As mentioned earlier, the highest values of the signal differentiation, *diff* (**ECG**), occurs precisely for samples located in the QRS complex. Therefore, once the highest slopes of the ECG signal can be associated to QRS samples along the ECG signal, they could be adequately identified.

The maximum absolute value of the difference between consecutive samples of the ECG signal corresponds to the parameter r_i which is related to *diff* (**ECG**) by the following expression:

$$r_i = \max\left|diff\left(\mathbf{ECG}\right)\right|, \quad (2)$$

where *i* is the subscript of the maximum slope within *diff* (**ECG**).The two consecutive samples ECG_i and ECG_{i+1} associated to r_i are adapted by using (3):

$$\begin{aligned} ECG_{corct,i} &= ECG_i - L_i, \\ ECG_{corct,i+1} &= ECG_{i+1} + L_i, \end{aligned} \quad (3)$$

where

$$L_i = r_i - thrs. \quad (4)$$

In (3), the sign of L_i is set positive when $ECG_i > ECG_{i+1}$, and vice-versa.

The signal **ECG** in equation (2) is then replaced by the modified signal $\mathbf{ECG_{corct}}$ which contains the adapted samples $ECG_{corct,i}$ and $ECG_{corct,i+1}$. (2), (3), and (4) are iteratively recalculated until $L_i \leq 0$. The decreasing value of r_i calculated at each iteration ensures the convergence of the parameter L_i. After the last iteration, all samples of **ECG** which have slope larger than *thrs* are adapted within $\mathbf{ECG_{corct}}$ and, therefore, match the samples of the QRS complex.

3.3 QRS Detector for Methodology Evaluation

The following QRS detector was implemented for evaluation of our methodology, according to the common algorithm structure proposed for QRS detection (Köhler et al., 2002):

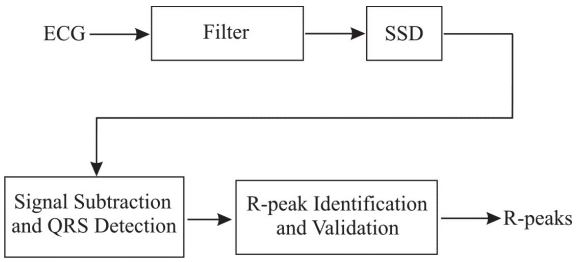

Figure 2: Block diagram structure of the QRS detector algorithm for methodology evaluation.

As observed in the diagram above, a filter is applied to the ECG signal before application of SSD. As is done with most QRS detector algorithms, a band-pass filter was used. This filter was set up as a 56-coefficient FIR, cut-off frequencies at 8 and 35 Hz. The reason to set the cut-off frequency at 35 Hz is because we noticed that a lower value causes considerable attenuation of the amplitude of QRS samples. This fact is in agreement with Thakor et al. (1984) which indicate that the bandwidth of the QRS complex ranges from 5 to around 40 Hz.

Application of the filter stage of figure 2 could be bypassed when the ECG signal is affected by

artefacts whose signal slope has order of magnitude much lower than the slope of the QRS samples, as discussed below.

3.4 Signal Subtraction and QRS Detection

As depicted in figure 2, after SSD approach described by (1) – (4) to be employed for adapting the samples associated to the QRS complex, a further subtraction stage is carried out for QRS samples selection, as follows:

$$\mathbf{P}_{sig} = \left| \mathbf{ECG}_{filt} - \mathbf{ECG}_{corct} \right|, \quad (5)$$

where $\mathbf{P}_{sig}$ contains the QRS selected samples. $\mathbf{ECG}_{filt}$ and $\mathbf{ECG}_{corct}$ correspond to the ECG signal after filtering and SSD application respectively. As SSD approach adapts samples with larger signal slopes associated to the QRS complex, the subtraction indicated in (5) excludes other regions of the ECG signal in such a way that the latter are represented as zero values within $\mathbf{P}_{sig}$. Therefore, the samples of $\mathbf{P}_{sig}$ whose value is different from zero are assumed to belong to the QRS complex.

3.5 R-peak Identification and Validation

Motion artefacts and drifting baselines are corrected during the subtraction performed in (5). Hence, the filtering stage shown in figure 2 could be used only when the signal is affected by artefacts whose signal slope is higher than *thrs*. Otherwise, there is no need for calculating another threshold for identification of the R-peaks as well. In this situation, since the samples of $\mathbf{P}_{sig}$ could be grouped in clusters corresponding to each QRS complex, the maximum sample amplitude of each cluster corresponds to the respective R-peak.

On the other hand, R-peak validation rules are demanded when the noise sample slope is higher than *thrs*, and calculation of a second threshold is also necessary. We tested a second threshold, *trp*, calculated taking into account the RMS value of the samples that belong to clusters corresponding to the last QRS complexes located. *trp* was set as being 50% of such a RMS value.

Also for peak validation, the minimum time between two consecutive clusters was set as 200 ms, considering the ECG refractory period. Thus, when two consecutive clusters along $\mathbf{P}_{sig}$ had a time difference lower than 200 ms, they were grouped into a unique cluster whose maximum sample amplitude was validated as identified R-peak.

3.6 QRS Detection Performance Analysis

According to Köhler et al. (2002), the usage of software QRS detection algorithms requires the evaluation of the detection performance. In this way, ANSI/AAMI/ISO EC57 (1998) recommends that the parameters sensitivity (*Se*) and positive predictivity (*+P*) should be calculated for algorithm assessment:

$$Se = \frac{TP}{TP + FN}, \quad (6)$$

$$+P = \frac{TP}{TP + FP}, \quad (7)$$

where *TP* is the number of true positives, *FN* the number of false negatives, and *FP* is the number of false positive QRS predictions.

4 RESULTS

Figure 3 illustrates the application of our methodology in the ECG excerpt of figure 1a.

For the signal shown in figure 3a, the band-pass filter was not applied in order to illustrate the application of our methodology to a raw ECG signal with high SNR. As observed in figure 3b, SSD approach adapts only ECG samples associated to the sharp wave activity of the QRS complexes whose slope is higher than *thrs*. Figure 4 depicts a zooming in around the time 811.5 s showing the samples identified as QRS samples.

Evaluation of our methodology was performed by application of the QRS detector of figure 2 to the recordings of the MIT-BH Noise Stress Test Database in accordance with ANSI/AAMI/ISO EC57 (1998). This database corresponds to twelve 30 min ECG recordings with different levels of SNR at 0, 6, 12, 18, 24, and -6 dB.

The results obtained for the parameters *Se* and *+P* are presented in table 1. The QRS detector shows high sensitivity (above 84%) even when the SNR is about -6 dB. Although the values obtained for *+P* are affected by a larger number of false positives which occur under low SNR conditions, the noise tolerance performance of such a detector is comparable to other ones proposed in the literature (Benitez et al., 2000); (Rezk et al., 2011).

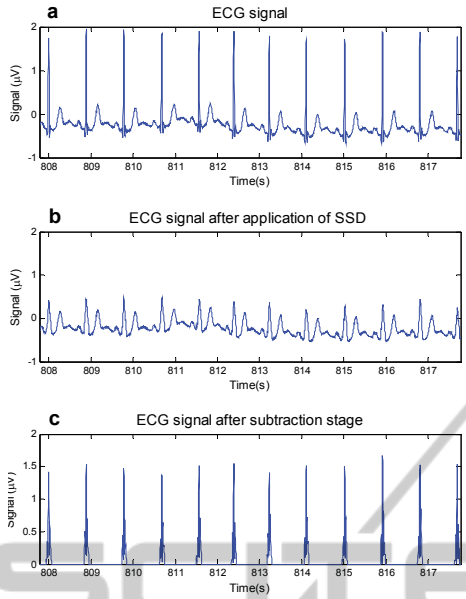

Figure 3: (a) ECG signal of figure 1a; (b) $\mathbf{ECG_{corct}}$, resulting from application of SSD to (a); (c) $\mathbf{P_{sig}}$ or absolute value of the subtraction between (a) and (b).

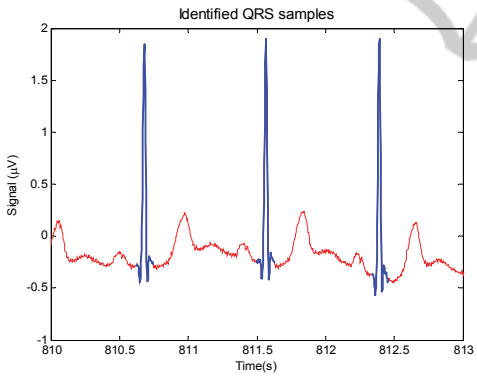

Figure 4: Zooming in figure 3a, around time 811.5 s. The regions of sharp wave activity with signal slope higher than *thrs* are identified as QRS samples (thick blue traces).

Table 1: *Se* and *+P* calculated for the MIT-BH Noise Stress Test Database considering application of the QRS detector depicted in figure 2.

Recording	*Se* (%)	*+P* (%)
118e00	91.62	79.33
118e06	98.24	86.24
118e12	99.96	93.47
118e18	99.96	98.91
118e24	99.96	99.56
118e_6	84.11	74.64
119e00	95.36	82.04
119e06	99.09	87.77
119e12	99.90	97.45
119e18	100	100
119e24	100	100
119e_6	85.51	71.96

5 DISCUSSION

As observed in figure 1, the difference between consecutive samples of the ECG signal can be used for identification of the shaper wave activity associated to QRS complex (Rangayyan, 2002). This property can be also observed in other biological signals or under specific conditions where the signal is affected by artefacts or other types of interference, as discussed by Cluitmans et al. (1993), Van de Velde et al. (1998), and Ferreira et al. (2012).

Ferreira et al. propose a methodology for detection and removal of gradient artefact residuals which also identifies artefact samples by the magnitude of the signal slope. Thus, we developed a modification of such a method for identification and selection of signal samples which contain sharp wave activity, described by equations (1) – (4). When applied to the ECG signal, these equations results in an effective identification of the QRS samples, as depicted in figures 3 and 4.

Application of our methodology within the prototype of QRS detector (figure 2) reveals that it has a good performance for identifying the R-peaks, even under conditions of low SNR (table 1). According to Arzeno et al. (2008), first-derivative-based methods can be easily implemented in real-time R-peak detection. Such advantage is also observed for the detector of figure 2. Moreover, it shows to be effective for detection of ectopic beats as well. Hence, in future work the performance of this QRS detector will be evaluated for a larger set of data and during removal of the ballistogram artefact as well, according to the approach proposed by Allen et al. (1998).

Therefore, the results shown in figures 3 and 4, and table 1 reflect the effectiveness of SSD in the detection of the steep wave activity of the QRS complex. This fact clearly indicates the possibility to apply the same approach to detect regions or artefacts in other biological signals which possess similar behaviour of the slope parameter. Identification of samples as belonging to the sharp wave activity region of interest depends on the value of the slope signal threshold, estimated by equation (1) for the ECG signal. Thus, our methodology achieves better performance when the slope of the sharp wave activity samples is higher and does not overlap the slope magnitude of other regions of the analysed signal.

Another fact which should be investigated in future work is how the application of SSD approach could be used to identify samples from a specific frequency bandwidth in the biological signal. For

example, in the case of the QRS complex region, this bandwidth ranges from around 5 to 40 Hz. In experiments which involve removal of gradient artefacts residuals from EEG signals, SSD shows to select higher frequency components associated to the artefact (Ritter et al., 2010; Ferreira et al. 2012). Thereby, SSD could be evaluated and proposed as an alternative time-domain filtering approach.

6 CONCLUSIONS

In this work, we propose a methodology (SSD) for detection of sharp wave activity in biological signals based upon differentiation of consecutive samples of the digital signal.

Our methodology shows to achieve effective identification of the sharp wave activity associated to the QRS samples in the ECG signal. Also evaluation of a QRS detector prototype which makes use of SSD reveals that the QRS complexes are localized with sensitivity and positive predictivity comparable to other methodologies proposed in the literature. In future work, our methodology shall be applied and evaluated for detection of sharp wave activity in other types of biological signals.

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