IMPROVING QRS DETECTION IN MULTI-CHANNEL ELECTROCARDIOGRAPHY BY PRINCIPAL COMPONENT ANALYSIS

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Abstract: We propose a QRS-enhancement and QRS detection method for multi-channel ECG recordings. The QRS-enhancement method combines the ECG data set into one signal in which the QRS complexes are enhanced and the noise is attenuated. The obtained QRS-enhanced signal always has an SNR that is better than the SNR of the average of the channels. The QRS detection method extracts a QRS template from the QRS-enhanced signal and finds QRS complexes by cross-correlating the template with the QRS-enhanced signal. Our results on abdominal ECG recordings indicate that especially in adverse recording situations where one or more channels display a large amount of noise and/or artifacts, our method is a valuable tool in multi-channel ECG recordings.

Introduction

The electrocardiogram (ECG) is commonly monitored for cardiac diagnosis, heart rate estimation, and arrhythmia detection. In automated ECG analysis the detection of the QRS complexes is essential as it is the prerequisite for the recognition of several ECG parameters like ECG intervals and wave amplitudes. Many methods have been proposed to accurately detect QRS complexes [1–9]. However, baseline wander, power line interference, electromyographic (EMG) interference, motion artifacts, and measurement noise hamper the QRS detection. In this paper, all these unwanted components will be referred to as noise. In exercise ECG, the noise is very pronounced due to the effects of respiration, skin resistance changes caused by the effects of respiration, and soft tissue movement affecting electrode contact. The use of multi-channel ECG systems offers the possibility of detecting the QRS complexes more reliably than by using only one channel. Although the shape of the QRS complex is highly dependent on the recording position on the patient's body, the delay between QRS occurrences in different channels is negligible. As a result, most of the QRS complexes are correlated in time for all channels. The noise in contrast often displays a negligible inter-channel correlation. By averaging the absolute values of the channels, which is a common procedure in multi-channel ECG recordings, this property is being exploited. However, this method only leads to a signal that is suitable for QRS detection if the amount of noise in all the channels is small enough. If one or more channels display a large amount of noise, this channel may significantly decrease the SNR of the resulting signal. Therefore, giving different weights to the channels when combining them for the purpose of QRS detection is favorable. The advantage of making a selection of the channels for QRS detection in adverse situations was already recognized by Kaiser [10]. However, his approach does not fully exploit the property of inter-channel correlation and requires a lot of computational power. In this paper we describe a method to automatically enhance the QRS complexes in a multi-channel ECG system by principal component analysis (PCA). This method generates a signal in which the correlated components in the channels, i.e., the QRS complexes, are enhanced. In addition, we propose a low-complexity QRS detection algorithm for the generated QRS-enhanced signal. We first discuss the basics of PCA and its performance in noise reduction. Then the QRS-enhancement and QRS-detection methods are explained in detail. The performance is demonstrated by applying our methods on abdominal ECG data and finally conclusions are drawn.

Principal Component Analysis

Basics

Principal Component Analysis (PCA) is a mathematical technique which transforms a data set into another data set with uncorrelated components called principal components. We denote by X a $[p \times q]$ data matrix consisting of q channels with p samples of data. We assume in this paper that all channels of X have zero mean. The first principal component $\underline{c}$ is by definition the linear combination of all the channels of X that yields maximum variance. By assembling the channel weights contributing to this linear combination in a $[q \times 1]$ column vector $\underline{u}_1$, $\underline{c}$ can be expressed as

$$\underline{c} = X \cdot \underline{u}_1, \tag{1}$$

with

$$\underline{u}_1 = \arg \max_{\|\underline{u}\|=1} \|X \cdot \underline{u}\|^2. \tag{2}$$

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The normalization constraint $\|\underline{u}\| = 1$ ensures that the maximum variance of $X \cdot \underline{u}$ is limited. When elaborating (2), it is found that vector $\underline{u}_1$ corresponds to the eigenvector of the covariance matrix of X belonging to the largest eigenvalue [11].

Noise reduction

In order to get more insight into the signal-to-noise ratio (SNR) features of the signal generated by PCA compared to a simple channel averaging procedure, we analyze a 3-channel ECG data set $X = [\ \underline{x}_1 \quad \underline{x}_2 \quad \underline{x}_3\ ]$ with different SNRs. The first two channels contain signals in noise with equal SNR, whereas channel 3 only contains noise n_3, i.e.,

$$\begin{aligned} \underline{x}_1 &= \underline{s}_1 + \underline{n}_1, \\ \underline{x}_2 &= \underline{s}_1 + \underline{n}_2, \\ \underline{x}_3 &= \underline{n}_3, \end{aligned}$$

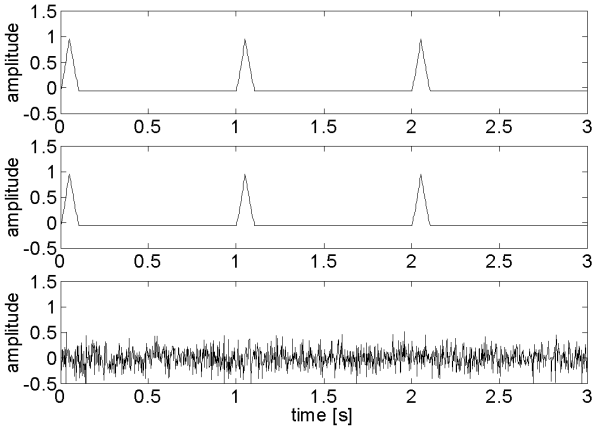
The noise $\underline{n}_3$ is uncorrelated to $\underline{s}_1$, $\underline{n}_1$, and $\underline{n}_2$. We assume that the variances of the channels are equal. The first principal component $\underline{c}$ is the combination of the channels that yields maximum variance. From all possible combinations, $\underline{u}_1 = \frac{1}{\sqrt{2}}[\ 1 \quad 1 \quad 0\ ]^T$ gives $\underline{c} = X \cdot \underline{u}_1$ the maximum variance. This first principal component direction vector is also the vector that gives $\underline{c}$ the maximum SNR, equal to $\mathrm{SNR}_{\underline{c}} = 2 \cdot \mathrm{SNR}_{\underline{x}_1}$. Simply averaging the channels results in a smaller SNR, i.e., $\mathrm{SNR}_{av} \leq (\frac{4}{3}) \cdot \mathrm{SNR}_{\underline{x}_1}$.

Similarly, it can be derived that for a data set containing channels with different SNRs PCA returns a signal $\underline{c}$ in which the channels with a larger SNR are represented more than the channels with a smaller SNR. As a result, the SNR of the signal obtained by PCA always exceeds the SNR of the averaged signal. Only in the case that the SNR of all channels is equal, the noise reduction by PCA and averaging is equal. In Fig. 1 this concept is visualized by means of a 3-channel data set with synthetic signals in which the channels have different SNRs.

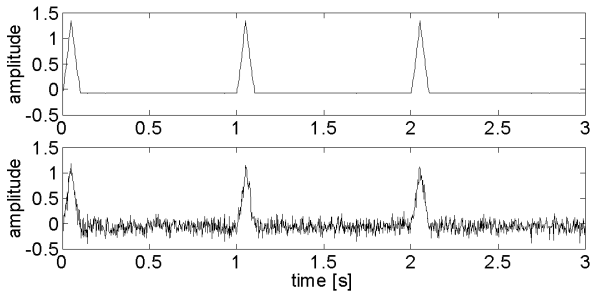
A calculation of the SNR of the average of the absolute values of the channels requires knowledge about the probability density functions of the signals and the noise. For simplicity reasons, this will not be evaluated further. Our expectation is that the SNR is about the same as the SNR of the average.

Normalization of channel variances

If the assumption of equal channel variances does not apply, the presence of one (or more) noisy channel(s) displaying a large variance may significantly decrease the performance of PCA in noise reduction. If the variance of one of the noisy channels is larger than the variance obtained by combining the channels with a large SNR, the largest PCA weight is attributed to the noisy channel with the largest variance. As a result, the first principal component has a SNR that is close to the SNR of the noisy channel. This can be avoided by normalizing the channels with respect to their variance before deriving the first principal component.



(a)



(b)

Figure 1: Illustration of noise reduction by PCA compared to averaging. Plot (a) shows a three channel data set with synthetic data. All channels have zero mean and equal variance. The first two channels contain a peaky periodic signal (SNR $= \infty$), while the third channel only contains white Gaussian noise (SNR $= -\infty$). Plot (b) shows the calculated first principal component (upper signal) and the average of all channels (lower signal). The first principal component clearly has a larger SNR than the average signal.

The normalized channels $\underline{x}_{N,j}$ $(j = \{1,2,...,q\})$ are created by dividing each channel $\underline{x}_j$ in X by its norm $\|\underline{x}_j\|$, i.e.,

$$\underline{x}_{N,j} = \frac{\underline{x}_j}{\|\underline{x}_j\|}. \tag{3}$$

Method

Multi-channel QRS enhancement method

The QRS enhancement algorithm is depicted in Fig. 2. It consists of a high pass filter (F), normalization step, and a PCA procedure. The input is a $[p \times q]$ data matrix X containing q ECG recordings of p samples.

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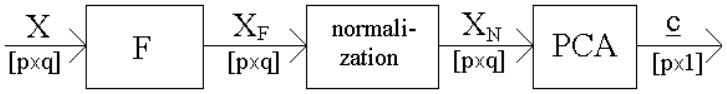

Figure 2: Block scheme of multi-channel QRS enhancement method. A data set X containing q channels with ECG recordings is filtered by a high pass filter F. The channels of the filtered data set X_F are normalized so that their variances are equal. The resulting normalized data set X_N is analyzed in a PCA procedure and its first principal component $\underline{c}$ corresponds to the QRS-enhanced signal.

All q channels in X are high-pass filtered with a steep FIR filter (Bartlett-Hanning window) containing 1000 taps. We found that a cut-off frequency of 3 Hz effectively removes the baseline fluctuations with a frequency below the cut-off frequency and hardly affects the amplitude of the QRS complex. Fig. 3 shows the magnitude characteristic of this filter.

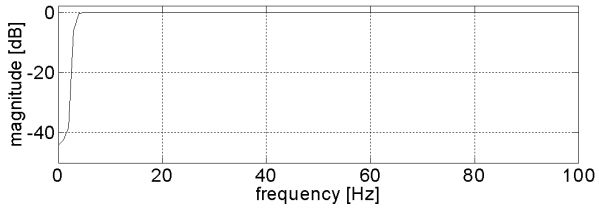

Figure 3: Magnitude characteristic of the high pass filter.

If the amount of baseline wander is limited, the number of taps can be reduced. This is favorable in case of online implementation. Then, all q channels are normalized such that the variances of all channels $\underline{x}_N$ in X_N are equal. For this step (3) is applied to $\underline{x}_N$. The PCA procedure returns the first principal component $\underline{c}$, being a linear combination of all normalized channels. As the variances of the channels are normalized, $\underline{c}$ is not determined by the variances of the separate channels. This prevents the negative impact of noisy channels with a large variance on the noise reduction performance of PCA. In the first principal component the correlated components, i.e., the QRS complexes, are enhanced and the uncorrelated components, i.e., the noise, are reduced compared to the average ratio of these components in the channels. Therefore, $\underline{c}$ will be referred to as the QRS-enhanced signal.

As large values for p highly increase the computation time for the PCA, it is desirable to calculate the first principal component direction $\underline{u}_1$ in the PCA on a subset of $[p_1 \times q]$ of X_N, with $p_1 < p$. The lower limit for p_1 is the number of samples needed to sufficiently represent the statistics of the channels. For (quasi-)periodic signals in stationary noise this lower limit corresponds to the number of samples in one period which is about 1 second for ECG signals. In that case, the obtained principal component direction vector $\underline{u}_1$ can be obtained from a subset $[p_1 \times q]$ of X_N after which $\underline{u}_1$ is applied to the whole $[p \times q]$ data set X_N.

QRS detection method

The QRS detection algorithm is depicted in Fig. 4. The QRS detection method is applied to the QRS-enhanced signal $\underline{c}$ and consists of a threshold operation and a cross-correlator. As a simple maximum amplitude detector can return shifted QRS positions in the presence of noise we use a cross-correlation based method. By cross-correlating a QRS template with the QRS-enhanced signal the uncorrelated noise is attenuated and the QRS complexes are further enhanced. This QRS template is obtained from the QRS-enhanced signal itself. Assuming that the minimum heart rate is 60 beats per minute (bpm), every segment of 1 second of $\underline{c}$ contains at least one QRS complex. Therefore, we take a window of 1 second of $\underline{c}$ and search for the sample with the maximum absolute amplitude. In this way, the polarity of the signal (i.e., upward or downward QRS complexes) is not relevant. This sample is taken as the center of a QRS template $\underline{t}$. The QRS template is created by the samples that lie within 0.05 seconds of this sample. In this way the QRS template has a length of 0.10 seconds, i.e., the normal duration of a QRS complex [12]. The elements r_m of the cross-correlation vector $\underline{r}$ between the QRS template and the QRS-enhanced signal itself are defined as

$$r_m = \Sigma_n t_{n+m} \cdot c_n. \tag{4}$$

By normalizing $\underline{r}$ we obtain that the cross-correlation value is exactly 1 when the template perfectly matches the windowed part of $\underline{c}$:

$$\underline{r}_N = \frac{\underline{r}}{\|\underline{t}\|^2}. \tag{5}$$

The value of $\underline{r}_N$ is close to 1 for the places where $\underline{c}$ has a shape that resembles the QRS template (see Fig. 5). Therefore, the samples for which $\underline{r}_N$ is larger than a threshold value χ are QRS candidates. The smaller the SNR of $\underline{c}$ the smaller χ should be. We empirically chose the threshold $\chi = \frac{1}{2}$. The sample with the cross-correlation closest to 1 of each group of successive samples gives the exact QRS position. Finally, heuristic rules may decrease the number of false detections. We assume that the maximal heart rate is 200 bpm implying that the time between two detected QRS complexes cannot be smaller than 0.3 seconds. In the case that two detected QRS complexes appear within 0.3 seconds after each other, the QRS complex with the cross-correlation value closest to 1 is retained, while the other one is rejected.

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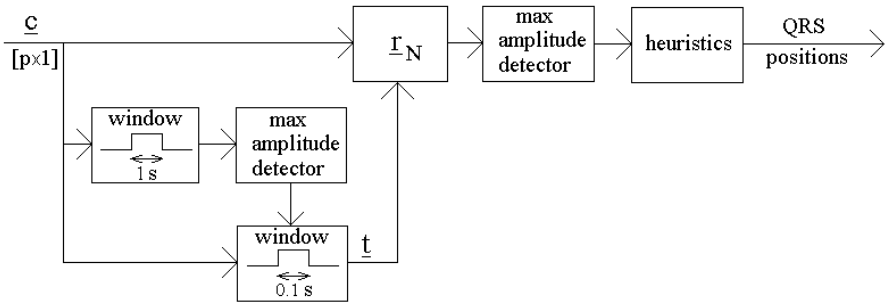

Figure 4: Block scheme of QRS detection method. The QRS-enhanced signal $\underline{c}$ is the input of the block scheme. In a window of 1 second of $\underline{c}$ the sample with the maximum amplitude is detected. With the samples around this sample a QRS template $\underline{t}$ with a length of 0.1 seconds is build. The maxima of the cross-correlation function between this template and $\underline{c}$ are QRS candidates. Heuristic rules eliminate false detected QRS complexes and retain the correctly detected QRS complexes.

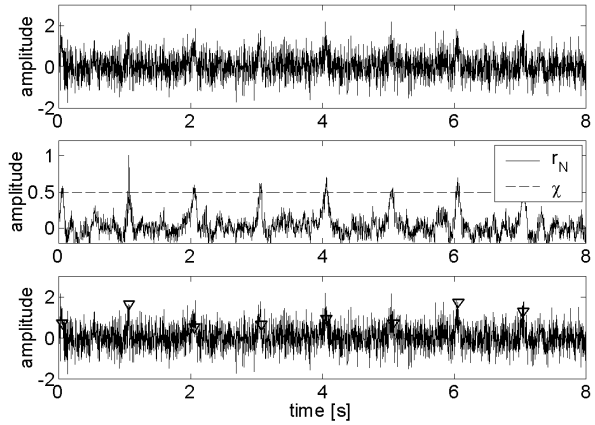

Figure 5: QRS detection method applied to the synthetic signal of Fig. 1, on which an amount of white noise is added such that the SNR is -10 dB. The upper plot shows the signal that goes into the QRS detector. In the middle plot the normalized cross-correlation (solid line) and the cross-correlation threshold (dashed line) are depicted. The lowest plot shows the signal again and the detected peaks (triangles).

Results

Our database consists of 15 data sets of 13-channel abdominal ECG recordings, each containing about 30 minutes of data. The recordings were sampled at 400 Hz and were made on pregnant women having a gestational age between 20 and 40 weeks. As a result, the recordings suffer from a large baseline wander, saturation effects, motion artifacts, and power line interference.

Our QRS enhancement method was applied to all 15 data sets. For each data set X, the first principal component direction vector $\underline{u}_1$ was derived from one second of data of X_N, i.e., after high pass filtering and normalization. This vector was applied to the whole data set X_N in order to obtain the first principal component. In addition, the average of the absolute values of the filtered data X_F was calculated. The QRS detection was applied to the QRS-enhanced signal and to the average of the absolute values of the channels.

The QRS detection performance was calculated as the percentage of outliers in the heart rate signal that is derived from the detected QRS complexes. For all the recordings, the heart rate signal was used as an indication for the actual range of the heart rate. Outliers were defined as heart rate values that clearly fall outside this range. The overall succes rate of detection was about 99% for our method and for the averaging method. We concluded that the overall SNR of the channels in the data sets was too large to properly investigate the added value of our PCA based method. Therefore, we also applied the methods to a subset of the data, i.e., 4 channels with a smaller overall SNR. This resulted in an overall success rate of 98 ($\pm$3)% and 93 ($\pm$10)% for our method and averaging, respectively.

In Fig. 6 and 7 the results of the methods on a number of selected channels of two of our abdominal recordings are depicted. Fig. 6(a) shows a short piece of a 3-channel ECG recording in which one of the channels merely contains noise. The average of the absolute values of all 3 channels after high pass filtering contains a large amount of the noise coming from channel 3. In contrast, the QRS-enhanced signal obtained by PCA consists of a combination of mainly the first two channels that clearly have a much larger SNR than channel 3. As a result, the SNR of the QRS-enhanced signal is significantly larger than the SNR of the average signal. As can be seen in 6(c), the QRS detection method is successful in the QRS-enhanced signal and even in the average signal for this small piece of data.

Fig. 7(a) shows a short piece of a 4-channel recording in which 2 of the 4 channels display a large amount of baseline wander and saturation effects. The high pass filter only partly removes the baseline wander as can be seen in Fig. 7(b). As a result, the average of the absolute values of all 4 channels gives errors in the QRS detection. In contrast, the weight factors of the PCA are such that mainly the two best channels for QRS detection contribute to the QRS-enhanced signal. As a result, our method returns a signal with a much larger SNR than the average signal (Fig. 7(c)). As can be expected, the QRS detection is successful for the QRS-enhanced signal but fails for the average signal.

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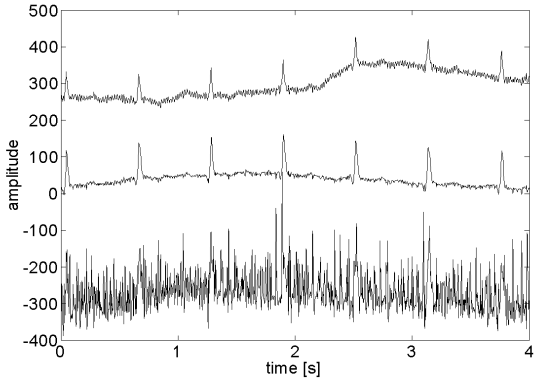
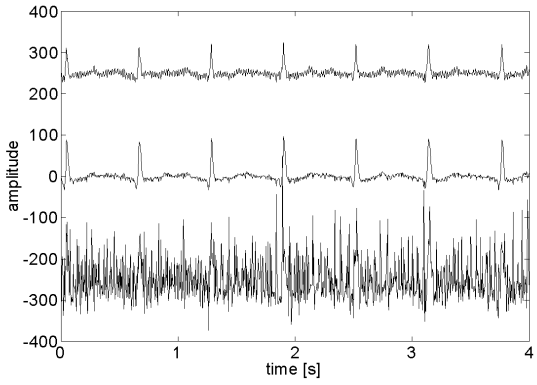


(a)



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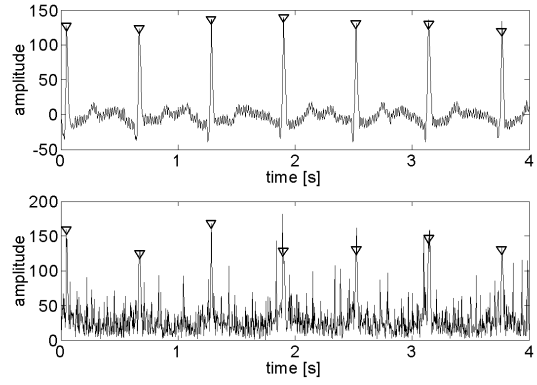
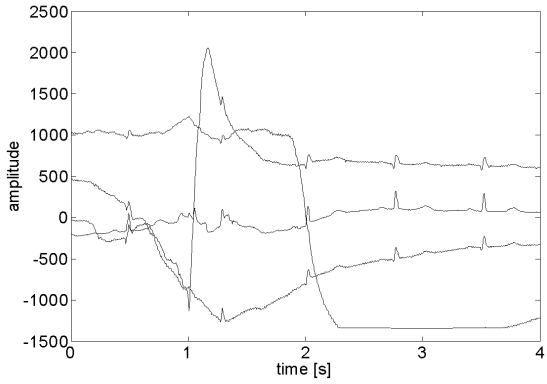
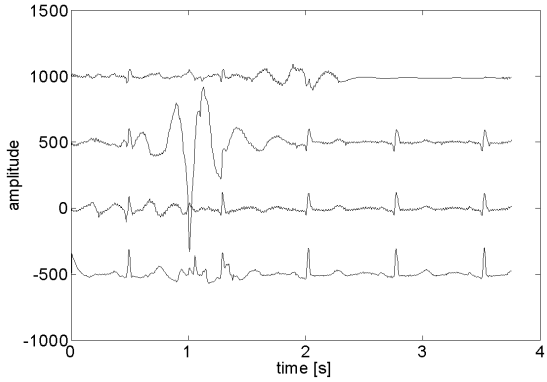


(c)

Figure 6: 3-Channel ECG recording where one channel displays a large amount of measurement noise and one channel displays power line interference. Plot (a) shows the original channels, (b) shows the channels after high pass filtering, (c) shows the calculated first principal component, with $\underline{u}_1 = \left[\, 0.7 \;\; 0.7 \;\; 0.3 \,\right]^T$ (upper signal) and the average of the absolute values of all channels (lower signal). The detected QRS complexes are indicated by triangles.



(a)



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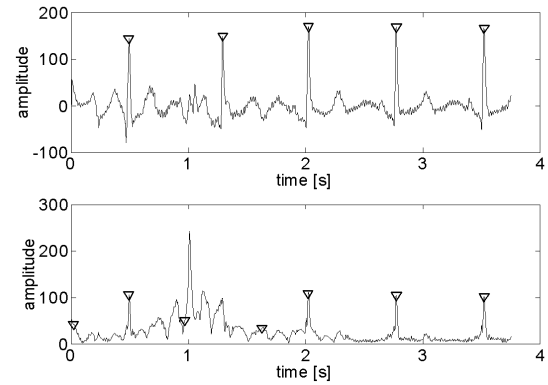

(c)

Figure 7: 4-Channel ECG recording displaying a large amount of baseline wander and saturation. Plot (a) shows the original channels, (b) shows the channels after high pass filtering, (c) shows the calculated first principal component, with $\underline{u}_1 = \left[\, 0.0 \;\; 0.1 \;\; 0.7 \;\; 0.7 \,\right]^T$ (upper signal) and the average of the absolute values of all channels (lower signal). The detected QRS complexes are indicated by triangles.

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Discussion

In this paper we propose a QRS-enhancement and a QRS detection method for multi-channel ECG recordings. The QRS-enhancement method combines a multi-channel ECG recording into one signal with special features without the need to manually select the best channels and exclude the channels with small SNR. In this signal the correlated components in the channels, i.e., the QRS complexes, are enhanced, and the uncorrelated noise components are attenuated. This QRS-enhanced signal is created by calculating the first principal component from the ECG data after high pass filtering the channels and normalizing the channel variances. The obtained QRS-enhanced signal has an SNR that is always better than the SNR of the channel-averaged signal. Especially in adverse recording situations in which one or more channels display a large amount of noise or artifacts, our method outperforms averaging. Only when the SNRs of all channels are equal, our method and averaging perform equally well with respect to noise reduction.

Our QRS detection method creates a QRS template from the QRS-enhanced signal based on maximum amplitude. This template is cross-correlated to the QRS-enhanced signal itself. QRS candidates are found by simply thresholding the cross-correlation amplitude. The heuristic rules that are implemented decide which QRS candidate is retained and which one is rejected. In this method, the creation of the template is the most critical step as it is taken as the golden standard for the QRS complexes. If the noise level is larger than the signal level in the QRS-enhanced signal the template creation may fail and, consequently, also the QRS detection.

Our methods have been applied to 15 abdominal ECG data sets containing channels with a large amount of baseline wander, segments of saturation, and uncorrelated noise. The methods were applied to the data after acquisition. The results of our method on these data sets are very promising. Yet further evaluation of our methods on even more adverse recording situations, e.g., exercise ECG recordings, capacitive ECG recordings, will give more insight about the benefits of our methods. In addition, a comparison of the QRS detection method to existing methods is necessary to draw further conclusions on its performance.

Future research will comprise an online implementation of the QRS-enhancement and QRS-detection methods, which is feasible as the computational cost is small. It should be noted that a delay of at least one second of data is required for our method when starting the analysis. In the QRS enhancement method, the data that enters the PCA should sufficiently reveal the statistics per channel. One second of data should be adequate for this purpose. In the QRS detection method, one second of data is needed for creating a QRS template. For some recordings a recurrent implementation of the QRS-enhancement method could be advantageous. E.g., if the noise in the channels is non-stationary, the optimal combination of the channels for QRS detection may not be constant. In that case, the first principal component direction vector should be updated from time to time. This recurrent implementation brings about a number of issues related to continuity of the QRS-enhanced signal and changing morphology and amplitude of the QRS complexes. These will also be assessed in our future research.

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