Heart Beat Detection in Multimodal Data Using Signal Recognition and Beat Location Estimation

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Abstract

The tachogram is typically constructed by detecting the R peaks in the electrocardiogram (ECG). Sometimes the ECG is however very noisy, which makes it hard to find the R peaks in these cases by using only the ECG. Information from other signals can then be used in order to find the R peaks. In this paper, a method is suggested that is able to automatically detect signals with the same periodic behavior as the ECG. Heart beat labels of the detected signals are combined by using majority voting, heart beat location estimation and Hjorth's mobility parameter. The average performance was 99.95% for the training set and 85.62% for the last phase of the 2014 Computing in Cardiology challenge. If the available labels for the signals are used, the performance on the hidden test set was 86.61%.

1. Introduction

The heart rate is one of the most important features that can be extracted from the ECG. This can be done by detecting the characteristic R peaks. Noise and artifacts can however interfere with the ECG, which makes it very hard to get accurate information from the R peak locations. Sometimes the ECG signal can even be completely useless by for example loose contacts or a defect sensor. In these cases, only using the ECG for heart beat detection is clearly not enough.

In multimodal datasets, information from other signals can be used in order to detect these R peak locations under noisy ECG conditions. Blood pressure (BP) and stroke volume (SV) signals can for example be acquired in a sleep monitoring application. Both these signals contain the same heart beat information and can also be used in order to estimate R peak locations. In this paper, we suggest a method that is able to detect these signals of interest automatically, assuming that at least one ECG signal is available.

The described method is used for participation in the 2014 Computing in Cardiology (CinC) challenge. For this challenge, the goal was to detect the R peaks in multimodal sleep monitoring data with ECG signals containing high noise levels. Processing was allowed to be offline, but a maximum computation time of 40s per record on the Physionet server was imposed [1].

Section 2 gives an overview of the used training and test data and the specific details of the 2014 CinC challenge. The different steps of the proposed heart beat detection algorithm are discussed in section 3. Finally the results are given and discussed in section 4.

2. Data-acquisition and challenge information

The methods were trained on the available multimodal training set, which contains 100 recordings of maximum 10 minutes. Signals including ECG, BP, SV, photoplethysmogram (PPG), electroencephalogram (EEG), electromyogram (EMG) and respiration (RESP) could be found in this training set. In this challenge, the first signal of the multimodal data was always guaranteed to be an ECG signal (see Figure 1). All the other signals could change for every recording in type and/or order of signals. Although the signals were labeled, mislabeling could occur.

The final results were obtained by applying the methods on a hidden test set of initially 100 records. The challenge proceeded in 3 stages. For the second and third stage, the hidden test set was enlarged with 100 new recordings, leading to a hidden test set of 300 recordings during the final stage. The sampling frequency could vary between 120Hz and 1000Hz.

3. Methodology

The procedure discussed in this paper is illustrated in Figure 1 and will be further explained in this section.

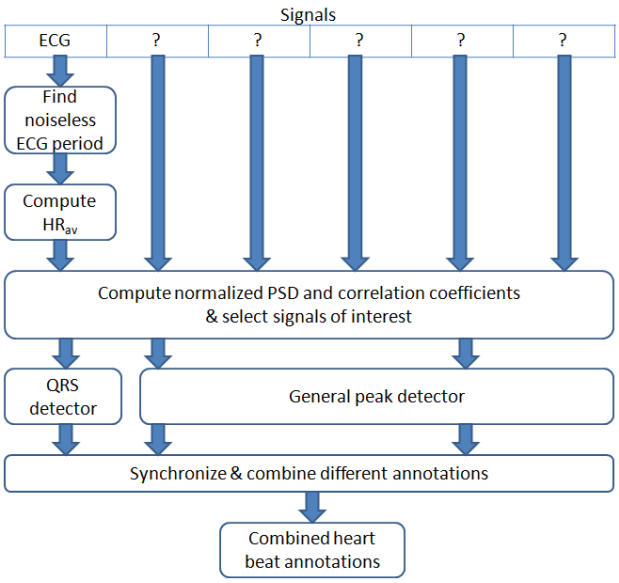


Figure 1. Overview of the procedure discussed in this paper. Only the signal type of the first signal is certainly known (ECG). In this example, signals 2 and 5 are detected as signals of interest for heart beat detection.

3.1. Automatic signal discovery

In the first step of the algorithm, the signals with the same periodic behavior as the ECG are automatically selected. By using this procedure, there is no need for using the given (possibly false) signal labels. These signals can be used in order to detect the heart beats in a more robust way. BP, PPG, SV and other ECG channels are examples of signals that show this behavior.

In order to do this, a segment of noiseless ECG (the first signal) is searched by using a similarity matrix of autocorrelation values of 5s ECG windows [2]. In order to get sufficient robust measurements, a segment of 1 minute (if available) was used in this paper. A R peak detection algorithm is applied just to this ECG segment and the average heart rate HR_{av} of this segment is obtained [3].

Next, the normalized power spectral density (PSD) is computed for all signals in this time segment. In order to get more robust PSD measurements, the signals are first processed with an envelope function. Signals with the same periodic behavior as the ECG should contain a peak in their PSD around the average heart rate frequency HR_{av}. Therefore, the normalized correlation coefficient between the PSD values in the interval $[HR_{av}$-0.3Hz, HR_{av}+0.3Hz] of the ECG signal and the other signals should be high enough. If this coefficient exceeds the threshold of 0.9, we assume the corresponding signal is a signal of interest. Only these signals will be processed from now on.

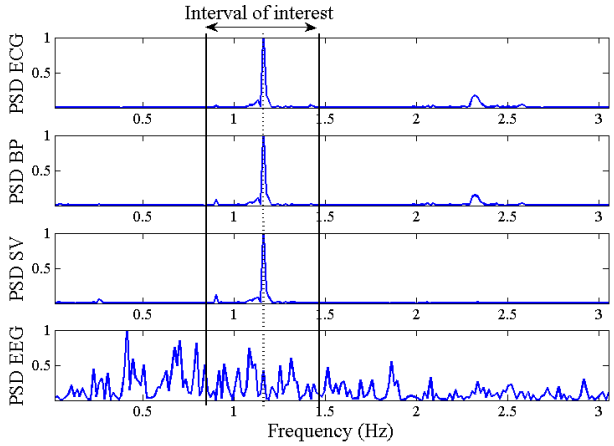


Figure 2. Illustration of PSD segments for ECG, BP, SV and EEG. The dotted line gives the average heart rate frequency HR_{av} in the found noiseless period in the ECG signal. The segment that is used for computing the correlation coefficient is marked by the bold vertical lines.

This procedure is illustrated in Figure 2. A clear peak in the PSD values can be found around HR_{av} for the signals of interest ECG, BP and SV. Clearly there is a completely different behavior in the PSD values of the EEG, which would lead to a low correlation coefficient and thus will not be selected. In this example, the frequency band may seem too large, but for some patients their heart rate varied so much that such a large frequency band was required for robust detection.

3.2. Individual peak detection

In the next phase, labels are found for each signal of interest for the entire record length. For the first signal, a specific QRS detection algorithm from the WFDB toolbox is used [1]. Another QRS detection algorithm is used here as it worked slightly better on a larger scale due to less influence of intensive RR-postprocessing. For the other signals, a basic peak detection algorithm is used. The algorithm consists of finding values that are higher than any other value in the surrounding neighborhood of 300ms. Despite its simplicity, it gave sufficient good results for peak detection in BP, PPG and SV in the training set, and a very low computation time was needed.

Because the peaks in the different signals do not occur at the same time, the acquired labels need to be synchronized in order to combine them in the next phase. The average delay between labels of the ECG and the other signals are computed and used for synchronization. If however the variance of the delay values is too high ($> 900s^2$), the signal is removed from the analysis. This may occur if a signal was falsely detected in the previous phase or if labels are not accurate enough.

Algorithm 1 Choosing best labels lab_i in $RR(n)$

if $est(n) > 6$
  Add $lab_i(n)$ with minimal Hjorth's mobility [4]
else if *any* $lab_i(n) = est(n)$
  Add $lab_i(n)$ with minimal distance to estimated labels
else if *any* $lab_i(n) = est(n) \pm 1$
  Add $lab_i(n)$ with minimal distance to estimated labels
else
  Add $lab_i(n)$ with minimal Hjorth's mobility
end if

3.3. Combination of labels

Finally, the different labels can be combined to result in a single list of labels. In order to do this, a signal x with the same length as the signals is used and its initial values are set to zero. For each label lab, the values $x(lab-window : lab + window)$ are increased with 1. For labels coming from the known ECG signal, $window$ equals 0.01s, for other labels it is set to 0.05s. This is due to the fact that BP and SV signals tend to contain less accurate labels (due to low frequency peaks) and could thus vary more compared to the corresponding R peak in the ECG signal.

When this signal x is constructed, we search for peak values above $\lfloor dim/2 \rfloor + 1$ in x, with dim the number of signals of interest (including the known ECG signal). If multiple equal values are found within one such peak, the central location is used for labeling. The different signals thus agree with strict majority on the correctness of these found labels. These labels are stored in the variable $peaks$.

Next, we run through $peaks$ chronologically, looking for a RR-interval in which possibly a heart beat is missed. The number of estimated missed heart beats $est(n)$ in a RR-interval $RR(n)$ from $peaks$ is estimated by

$$est(n) = \begin{cases} 0 & : val(n) \geq 1.5 \\ 1 & : 1.5 < val(n) < 2.6 \\ 2 & : 2.6 \leq val(n) < 3.5 \\ round(val(n)) - 1 & : else \end{cases}$$

with

$$val(n) = \frac{RR(n)}{median(RR(n-3:n-1))}$$

If $est(n) > 0$, the procedure in Algorithm 1 is used. The estimated labels are found by dividing RR(n) into $est(n)+1$ equal parts of length L. Only labels $lab_i(n), i \in [1, dim]$ coming from 1 signal can be added to $peaks$. Estimating the number of missing peaks becomes too hard if $est(n) > 6$, so Hjorth's mobility is directly used in this case [4]. It gives an indication on the smoothness of the tachogram. An example of this procedure is given in Figure 3.

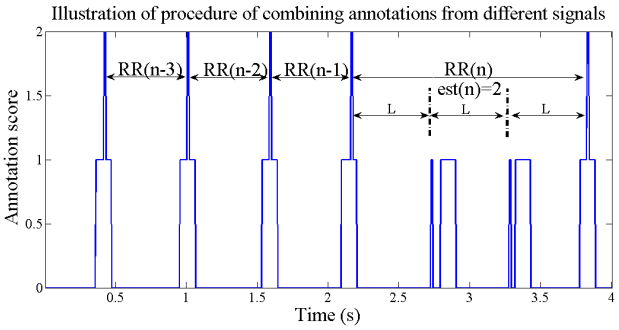


Figure 3. Illustration of the combination of labels of different signals. In this case, labels from ECG (narrow peaks) and BP (wide peaks) are combined. The dotted lines show the estimated R peak locations, which lay near the ECG labels. The ECG labels are thus added to $peaks$.

4. Results and discussion

The correctness of the automatic detection of signals of interest was only evaluated on the available training set. For this set, all BP, PPG and SV signals were correctly detected in the first step of the algorithm without causing any false positives (FPs) for signals like EEG or EMG. Some SV signals were removed in the second step because the delays had a too large variance. This was mainly the case in SV signals that did not show a smooth periodic behavior, which would not contribute to the peak detection. This indicates that this procedure indeed works as intended.

One of the main advantages of using the automatic detection of signals of interest is that the algorithm was also able to use new types of signals in the hidden test set. Signals like the phonocardiogram (PCG) could be detected with this method without occurring in the training set. The method was also able to detect signals that contain heavy interference from the QRS complexes. If these interferences were indeed strong enough, the R peaks in these signals could also be used for labeling. In general, the method can be used in order to do robust R peak detection in non-labeled multimodal datasets. The only requirement that is needed is the presence of one reference ECG signal.

Table 1 shows the results from the different datasets. The results of stage 1 of the competition were left out as the algorithm used for that stage was significantly different from the one described in this paper. Algorithm performance is evaluated by using the sensitivity (Se) and positive predictive value (+P). One of the main focuses of this paper was the automatic detection of signals of interest in order to avoid using mislabeled signals. Mislabeling however did not occur that often in the test set. Therefore, an extra version of the procedure was made that uses the signal labels in order to be more competitive for the 2014 CinC Challenge. In this case, the QRS detector was used

Stage	Training		Stage 2		Stage 3	
Labels?	N	Y	N	Y	N	Y
$Se_{gr}(\%)$	99.96	99.98	86.91	85.16	87.77	88.86
$+P_{gr}(\%)$	99.96	99.99	84.48	86.66	83.21	83.77
$Se_{av}(\%)$	99.95	99.98	86.22	85.71	87.53	88.53
$+P_{av}(\%)$	99.95	99.99	84.77	87.31	83.98	85.31
Overall(%)	99.95	99.99	85.59	86.21	85.62	86.61

Table 1. Results of the proposed algorithm on training set and hidden test set. Se_{gr} stands for gross sensitivity, Se_{av} for average sensitivity and similar for $+P_{gr}$ and $+P_{av}$ [1].

for every signal with an ECG label, the other peak detection algorithm was used on every BP or PPG labeled signal. SV signals were left out in this case as they tended to slightly decrease the performance. These results are also shown in Table 1.

It can be seen that the performance is reduced when no labels are used, but the effect is limited. A part of the decrease in performance might be due to the fact that for extra ECG signals a general peak detector is used rather than a specific QRS detector. The basic peak detector will typically add a number of FPs for some T-waves, increasing the chances of adding extra FPs during combination of the different labels. Another cause is the usage of SV labels. These labels are typically not that accurate due to the very low-frequency peak, which can lead to an label shift, resulting in 1 FP and 1 false negative for each heart beat. This problem was responsible for 65.6% of errors in the training step.

The general peak detection algorithm was rather basic in order to be able to detect peaks in multiple different signals of interest. As it was not known which type of signal is used, the algorithm should work for every possible signal of interest. The algorithm gave satisfactory results for BP, SV and PPG peak detection. Extra enhancements should be added in order to get similar results for ECG and PCG signals. This was however not yet implemented in the used procedure. It may be clear that by using more advanced peak detection algorithms and using the available labels, the performance can be further improved. This was however not the main goal of this paper due to the limited computation time. The algorithm that uses these signal labels finished third in the second stage and fifth in the final stage of the 2014 CinC challenge.

5. Conclusion

The proposed procedure is able to detect R peaks robustly in multimodal datasets. It is able to automatically detect the signals of interest for this goal without the need for labeled signals, and is able to detect new types of signals and signals containing high interference from R peaks. The labels of these signals are then successfully combined by a procedure containing majority voting, location estimation and Hjorth's mobility. The used procedure can be easily adapted in order to work in an online fashion with minimal computation constraints. Its performance can be further increased by optimizing the individual peak detection algorithms or by incorporating reliability scores to the different signals when constructing x.

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