DETECTING COMPONENTS OF AN ECG SIGNAL FOR SONIFICATION

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ABSTRACT

In recent state-of-the-art electocardiogram (ECG) studies, many authors mention that they had to manually correct automatically detected peaks or exclude artifact-loaded segments from the automatically annotated data they were studying. Given the importance of accurate feature detection for signal analysis, this is clearly a limiting factor. Our investigation into the use of sonification for analysis of ECG data for medical and diagnostic purposes is also hampered by the lack of such a reliable ground truth. In order to be able to undertake a comparative analysis of sonification and numerical techniques, we are investigating ways to improve algorithmic feature detection, particularly more robust algorithms for the detection of important landmarks in the signal in the presence of noise, whilst accounting for the variability in the very nature of the signal. This paper is a work-in-progress report of our efforts to date.

1. INTRODUCTION

The ECG is a single channel representation of the electrical activity of the heart muscle. It is a comparatively small voltage in the range 1-10 mV and sensitive to disturbances such as a subject's body position, breathing, interference from the mains power supply and from the data recording device and the pattern of placement of its electrodes.

An ECG signal is composed of a number of waves, as illustrated in Figure 1. It is produced by the autonomic interplay of the sympathetic (SNS) and parasympathetic nervous systems (PNS) through the sinoatrial node. The P-wave is the result of the excitation of the atria and the QRS-wave complex from that of the ventricles. During the ST-segment, no action potential is present in healthy subjects until repolarization, represented by the T-wave. An additional U-wave is not always visible and not shown.

ECG is the principal signal used to study the response of the heart under various conditions for a variety of clinical symptoms symptoms. Recently, there have been attempts to use Heart Rate Variability (HRV) analysis as an alternative to more cumbersome and expensive EEG techniques in related conditions, such as those related to breathing, such as sleep Aponea [1], including and experimental use of sonificationn[2]. In recent Heart Rate Variability (HRV) studies based on R-R interval measurements, Moersdorf

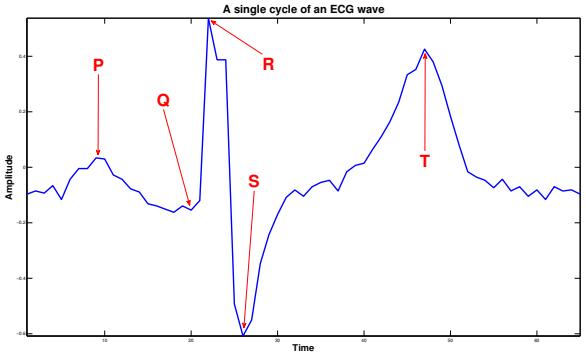

Figure 1: A single ECG wave cycle with the component P wave, QRS complex and T wave shown.

notes that many researchers reported that they had to manually correct the timing of automatically detected R-peaks or exclude artifact loaded data segments from their evaluation in the datasets they were studying. Given the importance of the accurate detection of such features to HRV analysis by whatever means, including, as in our work, by audification and sonification, there is a clear need for better approaches to signal feature detection [3]. We need to be able to objectively compare the effectiveness of using sonification for the identification of diagnostic features with purely numerical approaches, so we have tried to first improve the quality of the signal feature detection before sonifying for HRV analysis. This paper reports our initial approach to picking R-peaks using several signal processing techniques, including one adapted from feature detection in computational music analysis.

2. DATA PRE-PROCESSING TECHNIQUES IN PREPARATION FOR SONIFICATION

The data is processed for identification and enhancement of various landmarks within the ECG signal. We use ECG measurement recorded from a sleeping subject(for sleep apnea diagnosis). This data has a floating baseline and the occasional addition of noise due to the involuntary body movements of the subject. As a first task, we would like to process the signal to enable easy identification of the R-peak from a QRS complex. A block diagram of the steps involved in the pre-processing of the signal is shown in Figure 2. The input signal has a sampling rate of $100Hz$. The following steps are performed to detect the R-peak.

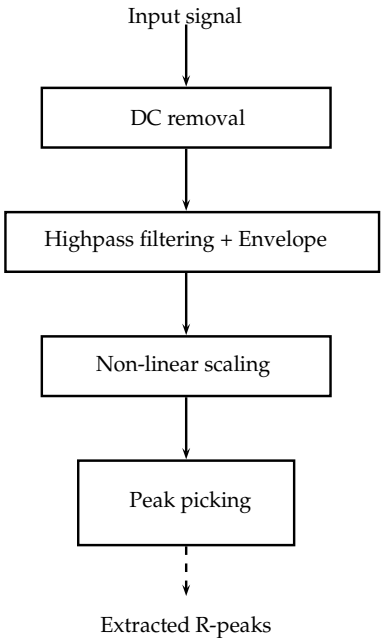

Figure 2: Block diagram of the pre-processing technique

2.1. Median bias removal

The signal $x[n]$ is median filtered with a $M = 2L+1$ point median filter, where $L = 20$ is chosen. The value of $L = 20$ is used since the QRS complex is usually of $20 - 30$ samples. We intend to retain the QRS complex and suppress the P and T wave s. Since the R-peak has a much shorter duration than the P and T waves this selective enhancement is possible through a carefully chosen median filter.

$$x_{med}[n] = median\{x[n-L], x[n-L+1]...x[n+L]\}, \quad (1)$$

where x_{med} is the median filtered signal. The bias is removed by subtracting $x_{med}[n]$ from $x[n]$,

$$x_c[n] = x[n] - x_{med}[n], \quad (2)$$

where $x_c[n]$ is the bias corrected signal. A median filter is preferred over a mean filtering operation, since it can easily estimate the long term floating baseline in all regions while suppressing the peaky QRS complex effectively. Thus the subtraction operation with the median filtered version of the signal does not significantly alter the shape of the QRS complex much. The signal may contain P and T peaks with amplitudes comparable to the R-peak, under certain conditions. It is further processed to selectively attenuate the P and T peaks without harming the R-peaks.

2.2. Linear Filtering and Non-Linear Scaling

An FIR filter of order 2 is applied to the signal $x_c[n]$, to suppress the P and T peaks since they vary slowly compared with the R-peak[4].

$$x_e[n] = x_c[n] * f[n], \quad (3)$$

where $f[n]$ is the high pass filter and $x_e[n]$ is the enhanced signal. The enhanced signal is now full wave rectified to accentuate the presence of the R-peak. An envelope estimation process is needed to pick strong peaks and we perform the Hilbert transform operation to estimate the envelope. This signal is further scaled non-linearly. This scaling allows us to locate the R-peaks easily for further processing, while suppressing any spurious regions in the signal. Let $\mathcal{F}$ denote the non-linear scaling transfer function. Then,

$$x_{nls}[n] = \mathcal{F}(x_e[n]), \quad (4)$$

where $x_{nls}[n]$ represents the non-linear scaled signal. This signal is used as input to a peak picking algorithm to detect R-peaks accurately.

2.3. Peak picking and grouping

The high pass filtering followed by Hilbert envelope computation and non-linear scaling allows for easy picking of the R-peaks. Even some peaks with low amplitude, buried in noise are easily detectable. The peaks are picked as local maxima above a threshold of 0.2, in the function $x_{nls}[n]$. Peaks that are closer than $400ms$ are grouped together. This removes many double peaks that the modified signal may have. From the signal $x[n]$, we extract the peak closest to a peak found in $x_{nls}[n]$, since the high pass filtering and Hilbert envelope computation leads to detection of peaks in $x_{nls}[n]$ which are offset by a few samples. These adjusted peaks are then extracted for sonification purposes. A plot encapsulating the signal reduction from its original form to the R-peaks is shown in Figure 3.

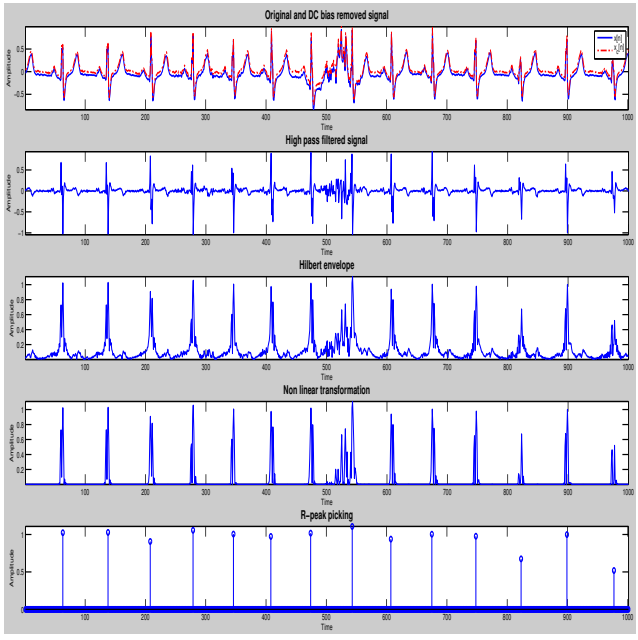

Figure 3: Signal transformation leading to detection of R-peaks: (a) Original (blue) and DC bias removed(red -.) signal (b) High pass filtered signal (c) Hilbert envelope (d) Non-linear transformation of Hilbert envelope (e) Peak picking

3. RESULTS

We compared the performance of the peak picking algorithm for a single ECG file of 8 hours from the Physionet Sleep Apnea Database [5]. It was recorded at a sampling rate of $100Hz$ and has 39,682 annotated R-peaks. We use the measures of performance usually applied in the ECG community, namely Sensitivity (Se) and Positive predictivity (+P) for evaluating our algorithm against the annotation [1]. The measures along with F-measure are tabulated for various window lengths in Table 1. The window length, in time, around the annotation that a R-peak is searched for, is represented by δ. We explore the possibility of the peak picked being very close to the annotation by restricting the window lengths to one of $\{10ms, 20ms, 30ms\}$. At the sampling rate of the data, this corresponds to the annotated peak and picked peak being off by 1 sample, 2 samples or 3 samples respectively. As can be seen the techniques presented above lead to good precision even though the data is noisy. We are currently investigating the application of other algorithms for improving R and other peak-picking in even noisier conditions but the results are inconclusive at this stage and the techniques subject of further investigation.

δ in secs	+P	Se	F = 2.(+P).Se/((+P)+Se)
0.01	39.7	39.1	39.4
0.02	97.3	96.0	96.7
0.03	99.6	98.2	98.9

Table 1: The Positive predictivity(+P), Sensitivity(Se) and F measures for performance of the R-peak detection algorithm for various window lengths.

4. CONCLUSIONS

In this paper, we applied some well known techniques used in data reduction for accurately picking the R-peaks from a QRS complex of an ECG signal, as an initial step towards landmark identification. The resulting signal is easy to handle in terms of locating landmarks and performs well in moderately noisy conditions. We intend to explore other noise removal techniques, signal enhancement algorithms and test them on a wider variety of datasets.

5. REFERENCES

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