MULTI-PARAMETER DETECTION OF ECTOPIC HEART BEATS

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ABSTRACT

We analyse features from R waveform of electrocardiogram (ECG) and blood pressure (BP) signals for intelligent detection of ectopic (premature) heart beats. Detection of these beats are important are they could be pre-cursor for serious arrhythmias. The combination of ECG and blood pressure signals to detect ectopic heart beats are relatively new as most methods use only ECG signals. Two new features, mobility and complexity factor (used in electroencephalogram analysis) derived from R waveform of ECG signal are studied in addition to the conventional ECG and BP features. Three cases of beats are considered: 2 ectopic - premature ventricular contraction (PVC) and premature supraventricular contraction (PSC) and normal (N). All the features are normalized with some factor inherent in the signal to reduce the inter-subject variance of the features. Data from 50 subjects totaling 3000 beats (1000 N, 1000 PSC and 1000 PVC) from Massachusetts General Hospital/Marquette Foundation database are used. The 13 features were classified by the Multilayer Perceptron - Backpropagation neural network into the 3 classes. The results gave classification performance up to 96.47%. It is concluded that ECG and BP features could be used to detect ectopic beats successfully.

1. INTRODUCTION

The electrical impulses that initiate the normal heart beats start from the sinoatrial (SA) node. Ectopic or premature heart beats are those that originate from non-SA locations. They could be classified into two general categories: one with ventricle origin and the other non-ventricular origin [1]. The earlier is known as premature ventricular contraction (PVC), while the latter is known as premature supraventricular contraction (PSC). PSC has its origin either in the atrial or junctional (nodal). Both atrial and junctional premature beats are commonly grouped together because of their similar electrocardiogram (ECG) waveforms. The occurrences of ectopic heart beats are not life threatening as in the case of ventricular fibrillation (VF) rhythms but signify problems with the heart and some forms of ectopics can indicate a predisposition to life-threatening arrhythmias [1]. For example, frequent occurrences of PVC (> 6 beats per minute) may lead to VF. Therefore, early and accurate detection of these beats may save lives. However, detection of these beats are time-consuming because of the occasional nature of occurrence and intelligent and automated computer based detection would be an advantage especially in long-term patient monitoring.

In this study, our aim is to derive features from R waveform of ECG and blood pressure (BP) features to detect these ectopic beats. Most ectopic beat detection methods [2-4] use only ECG signals. However, it is known that stroke volume changes after the occurrence of these beats and as such cause variations in blood pressure (BP) waveforms [5]. For example, the arterial blood pressure (ABP) generally drops after ectopic beat. Therefore, measuring the changes in ABP before and after the occurrence of these beats would be a suitable feature to distinguish between normal and these ectopic beats.

We use the conventional R waveform features like R-R interval and R amplitude. In addition, we propose the use of two new features, mobility and complexity factor computed from R waveform. These two features have been proposed by Hjorth [6] for electroencephalogram (EEG) analysis. Next, numerous features from ABP signal are computed. All the features are then normalized with some factor inherent in either the ECG or ABP signals. This is important to reduce the inter-subject variance.

Data from 50 subjects (tapes mgh001- mgh050) from the Massachusetts General Hospital/Marquette Foundation (MGH/MF) database are used. Noise reduction algorithms are applied to both ECG lead I and ABP signals. A total of 3000 beats comprising of 1000 normal (N), 1000 PVC and 1000 PSC beats are extracted. For each beat, features are computed. These data are split equally into two sets, one for Multilayer Perceptron - Backpropagation (MLP-BP) [7] neural network training and the other for MLP-BP testing.

2. METHODOLOGY

2.1. Data

Data from tapes mgh001-mgh050 from MGH/MF database were used because these tapes contained the largest number of PSC or PVC or both types of beats. The database actually contains 8 signals as could be seen from Figure 1. However, in this study, we considered only signals from ECG lead I and ABP. A total of 1000 pattern files from each N, PSC and PVC beats were extracted using the supplied beat annotation files where the pattern files consisted of

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ECG lead I and BP signals from four beats: two beats before the beat being studied and one beat after the beat being studied. Data from some subjects had to be discarded from the study due to the errors in the data.

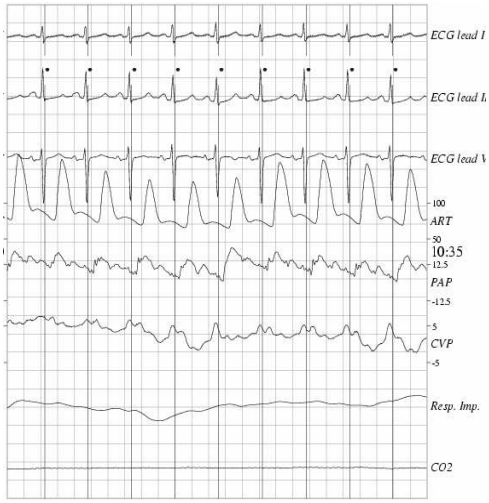

Figure 1. Signals in MGH/MF database

2.1. ECG Pre-processing

An example of the extracted ECG signal and ABP signal are shown in Figure 2. As could be seen the figures, there is a lot of noise. Three commonly encountered noises are high frequency noise, 60 Hz powerline interference and baseline wander. These noises have to removed in order for accurate extraction of features from ECG signals. Forward and reverse Butterworth IIR filter (with different pass-band frequency ranges) for both the ECG and ABP signals are used for this purpose. Forward and reverse filtering are performed to avoid phase distortion caused by the Butterworth filter, which is a non-linear filter. This procedure of forward and reverse filtering is done for all times when Butterworth filter is used in this paper. In all the cases using Butterworth filter, minimum attenuation of 30 dB is achieved in the stopband using the respective orders.

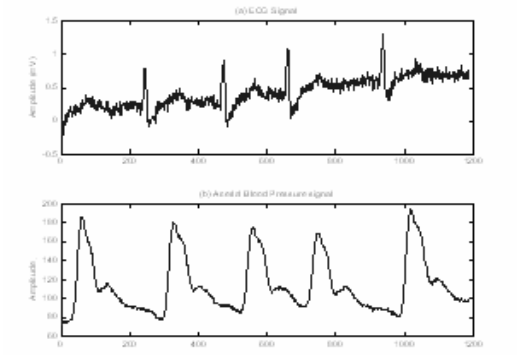

Figure 2. Examples of extracted ECG and ABP signals (consisting of 4 beats)

ECG signal is low-pass filtered to remove high frequency noises using a 13th order Butterworth digital filter with 3 dB cut-off at 35 Hz. Order 13 is used to obtain attenuation of 30 dB at 40 Hz. This cut-off frequency is chosen based on studies in [3]. Baseline wander is caused by subject movement or perspiration. To remove this type of noise, we use a 5th order high-pass Butterworth digital filter with cut-off at 1 Hz. Order 5 is enough to attenuate the signals completely beyond 2 Hz.

Similar to ECG signals, ABP signals were also pre-processed to reduce noise. ABP signals were bandpass filtered from 0.5 to 15 Hz using a low-pass and high-pass Butterworth digital filter. The frequency range is chosen following the approach in [9]. Figure 3 and 4 show examples of the original ECG and ABP signals, and after reducing the noises.

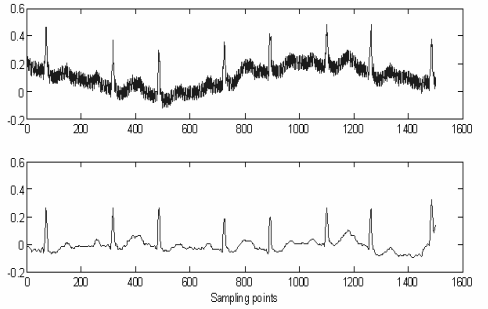

Figure 3. An example of (a) original ECG signal, (b) after noise reduction

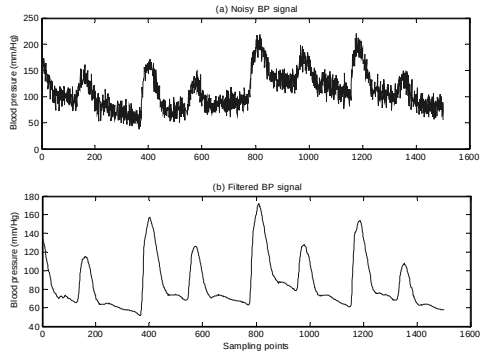

Figure 4. An example of (a) original ABP signal, (b) after noise reduction

2.2. Feature extraction

QRS complex of ECG signal is detected using modified Pan and Thomkins (PT) algorithm [8]. The difference to PT algorithm is that the ECG signal is bandpass fitered from 7-14 Hz using 9th order Butterworth filter. The rest of the processes like squaring, window integration and thresholding are similar to PT. Window integration length of 54 samples (150 ms) are used. Once the R peak is detected (the maximum peak in the threshold window), the peaks Q and S are detected using simple

peak detection methods. Peak Q is assumed to lie within 50 ms before R peak, while S peak is assumed to lie within 100 ms after R peak. R amplitude (Ra), R-R interval (RRint), mobility (MB) and complexity factor (CF) are computed from the ECG signal. MB [6] is defined as

$$MB = \sqrt{\frac{\mathrm{var}(x')}{\mathrm{var}(x)}}, \quad (1)$$

where x is the original ECG signal from points Q to S, while x' is the first derivative of this Q-S ECG segment. MB is basically a ratio of energy of higher frequency signal over the energy of the signal. Since ectopic beats have longer QS segments, so the higher frequency energy will be lower. Therefore, MB of N will be higher than PVC and PSC.

CF [6] is defined as

$$CF = \sqrt{\frac{MB(x'')}{MB(x')}}, \quad (2)$$

where x'' is the second derivative of this Q-S ECG segment. CF represents the complexity of the signal. It is actually a ratio of square of higher frequency energy over energy of the signal multiplied by highest frequency energy. It is known that PVC signals exhibit bizarre electrical waveforms and as such should have highest complexity among the three different classes of beats that are studied.

The systolic (peak) and diastolic (trough) values were detected by simple peak and trough detection methods. The pre and post systolic pressure (SP) and diastolic pressure (DP) values were used to compute the other parameters like Mean Arterial Pressure (MAP) and Pulse Pressure (PP) where

$$\mathrm{MAP} = \mathrm{DP} + 1/3*\mathrm{SP} - \mathrm{DP}, \text{ and} \quad (3)$$

$$\mathrm{PP} = \mathrm{SP} - \mathrm{DP}. \quad (4)$$

All these parameters are then used to compute the normalised features as shown in Table 1. The term 'abs' and 'delta' refer to absolute value and change in value, respectively while the subscript 'N' refers to values obtained from a normal beat in the same file.

2.3. MLP-BP classifier

MLP neural network trained by the BP algorithm is used to classify the computed features into either normal, PSC or PVC categories. Half of the data (1500 patterns) are used to train the network while the rest half (1500 patterns) are used in testing. The hidden nodes are varied from 10 to 50 nodes in steps of 10. The input layer consisted of 13 nodes because the number of features is 13, while the output layer is set to 3 nodes for the three classes. The target output for the trained pattern is set to 1.0, while for the rest of the classes, it is set to 0. Training is conducted until the average error falls below 0.01 or the maximum iteration limit of 1000 is reached. Figure 5 shows the architecture of the MLP-BP network architecture as used in this study.

Table 1. Normalised features used in this study

No.	Feature
1	Ra/Ra_N
2	Post R-Rint/$R\text{-}Rint_N$
3	Pre R-Rint/$R\text{-}Rint_N$
4	MB/MB_N
5	CF/CF_N
6	Delta MAP = (Pre MAP - Post MAP)/abs MAP_N
7	Delta PP = (Pre PP - Post PP)/abs PP_N
8	Delta DP = (Pre DP - Post DP)/abs DP_N
9	Delta SP = (Pre SP - Post SP)/abs DP_N
10	Post DP/DP_N
11	Pre DP/DP_N
12	Post SP/SP_N
13	Pre SP/SP_N

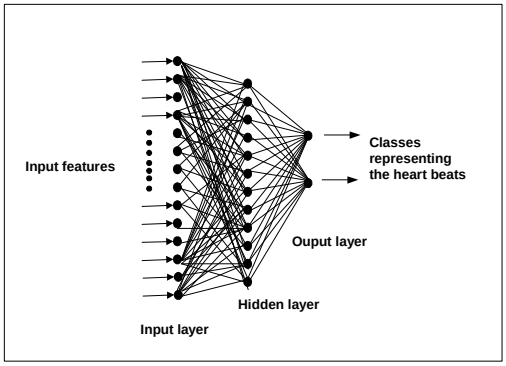

Figure 5. MLP-BP neural network architecture as used in this study

3. RESULTS

Table 2 shows the MLP-BP classification results for the varying hidden units. As could be seen from Table 1, the performances do not vary much with different hidden modes. The best performance of 96.47% is achieved for 50 hidden nodes. The whole process of pre-processing, feature extraction and classification takes less than a second when run on P4 machine with MATLAB (Mathworks, Inc.) codes. Therefore, the method could be applied for real-time heart beat detection.

4. CONCLUSION

In this study, we have extracted features from lead I ECG and ABP signals to detect ectopic beats. Manual detection of these beats is difficult because of the occasional occurrence of the beats. Therefore, automatic accurate detection of these beats may give an early warning for further diagnosis of serious life