DETECTION OF ECTOPIC HEART BEATS USING ECG AND BLOOD PRESSURE SIGNALS

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ABSTRACT

In this paper, we propose using a combination of ECG and blood pressure signals to detect ectopic heart beats, specifically premature supraventricular and ventricular contractions (PSC and PVC). Detection of these beats are important are they could be pre-cursor for serious arrhythmias. Common detection methods of these beats use only ECG signals. However, the stroke volume changes after the occurrence of these beats, which results in blood pressure variations. Following this fact, we combined features extracted from QRS complex of ECG signal Lead I with systolic and diastolic arterial blood pressure values to classify normal, PSC and PVC beats. Data from 5 subjects totaling 750 beats (250 normal, 250 PSC and 250 PVC) from Massachusetts General Hospital/Marquette Foundation (MGH/MF) database were used. The data were split equally for Multilayer Perceptron - Backpropagation (MLP-BP) neural network training and testing. The combined features were classified by the MLP-BP neural network into the 3 classes. The features were normalized using some parameter inherent in the signals. This was to normalize the features across different subjects. The results gave classification performance up to 92.00%. It is concluded that ECG and blood pressure features could detect PSC and PVC.

1. INTRODUCTION

Premature Supraventricular and Ventricular Contractions (PSC and PVC) are two common ectopic beats. The occurrences of these heart beats are not life threatening like ventricular fibrillation rhythms but signify problems with the heart and some forms of ectopics can indicate a predisposition to life-threatening arrhythmias [1]. 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 computer based detection would be an advantage especially in long-term patient monitoring.

The common heart beat detection techniques use only ECG leads [2-4]. Here, we use ECG signal in combination with blood pressure signal. This is only logical since the stroke volume changes after the occurrence of these beats and as such cause variations in blood pressure (BP) waveforms [5]. For example, the systolic arterial pressure generally drops after PVC or PSC. Therefore, measuring the change of systolic blood pressure (SBP) and diastolic blood pressure (DBP) before and after the occurrence of PVC or PSC would be a suitable feature to distinguish between normal and these ectopic beats.

Data from 5 subjects from the Massachusetts General Hospital/Marquette Foundation (MGH/MF) database are used. Noise reduction algorithms are applied to both ECG lead I and arterial BP signals. A total of 750 beats comprising of 250 normal, 250 PSC and 250 PVC beats are extracted. For each beat, QRS complex is detected and features like R amplitude, pre and post R-R intervals, pre and post delta R-R interval were computed. Next, pre and post SBP and DBP values are computed.

These data are split equally into two sets, one for Multilayer Perceptron - Backpropagation (MLP-BP) [6] neural network training and the other for MLP-BP testing.

2. METHODOLOGY

Data from tapes mgh002, mgh004, mgh010, mgh011, mgh018 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 arterial BP. A total of 250 pattern files from each normal, PSC and PVC beats were extracted using the supplied beat annotation files where the pattern files consisted of ECG lead I and BP signals from four beats: two beats before the beat being studied and one beat after the beat being studied.

2.1. ECG Pre-processing

An example of the extracted ECG signal and BP 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 noise have to removed in order for accurate extraction of features from ECG signals.

For the ECG signal, a notch filter using the equation

$$y(n) = x(n) - x(n-1) + x(n-2), \qquad (1)$$

was used to filter out the 60 Hz noise where *x(n)* is the ECG signal and the sampling frequency is 360 Hz. The output signal might still contain some components near 60 Hz but these will be removed in the next step.

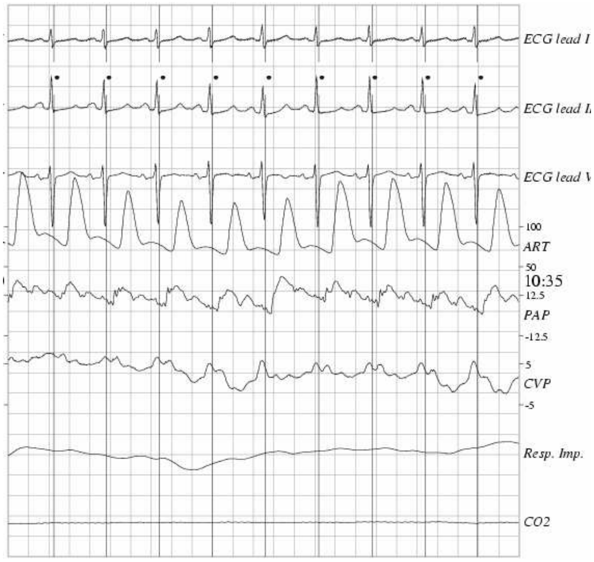

Fig.1 Signals in MGH/MF database

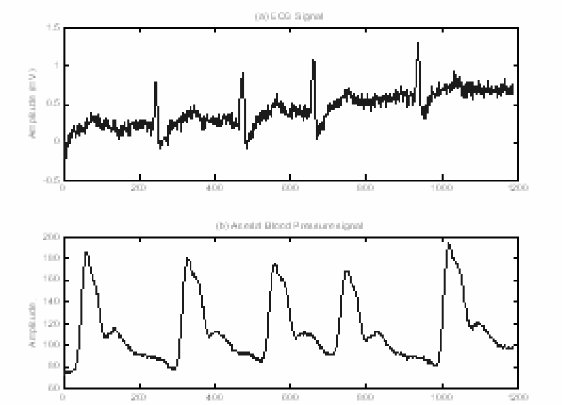

Fig.2 Examples of extracted ECG and BP signals (consisting of 4 beats)

Next, the signal was low-pass filtered to remove high frequency noises using a 13^{th} order Butterworth digital filter with 3 dB cut-off at 35 Hz. Order 13 was used to obtain attenuation of 30 dB at 40 Hz. This cut-off frequency was chosen based on studies in [3]. Because Butterworth filter is a type of Infinite Impulse Response (IIR) filter, which causes phase distortion, the output of the filter was run back through the filter to offset the phase distortion. This procedure of forward and reverse filtering was done for all times when Butterworth filter was used in this paper.

Baseline wander is caused by subject movement or perspiration. To remove this type of noise, which has a very low spectral range, we first extracted the baseline noise. This was done using a 6^{th} order low-pass Butterworth digital filter with cut-off at 1 Hz. Order 6 was enough to attenuate the signals completely beyond 2 Hz. Once the baseline signal has been detected, the clean signal was obtained by subtracting the baseline signal from the original signal.

Figure 3 shows an example of the original ECG signal, ECG signal after reducing 60 Hz noise and after reducing the baseline wander.

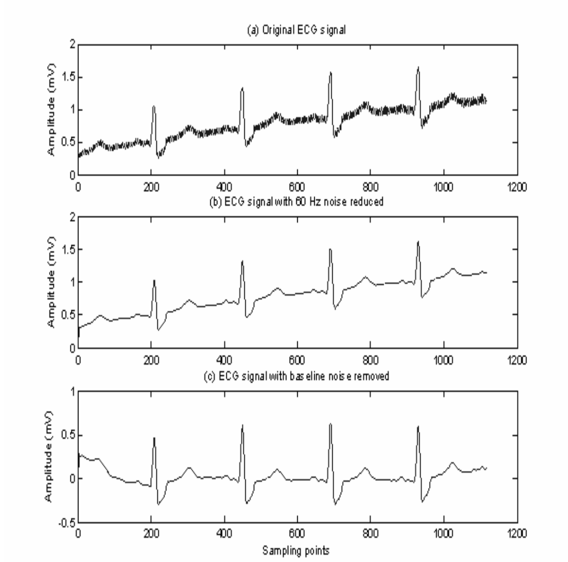

Fig.3 An example of (a) original ECG signal, (b) after 60 Hz noise reduction (c) after baseline noise reduction

2.2. ECG feature extraction

Pan and Thompkins algorithm [7] was used to detect the QRS segment. The algorithm was modified slightly where the low-pass and high-pass filters used in the algorithm have been replaced by a 6^{th} order bandpass Butterworth digital filter with 3 dB cut-off from 7-14 Hz. This range was chosen because our studies showed that R peaks have spectral range around 11 Hz. The rest of the steps used here like squaring, moving window integration and thresholding were the same as Pan and Thompkins algorithm. Moving window integration length, N was set at 54[1] and thresholding value was set at 3.0. Threshold value was reduced by 0.5 recursively if a R peak is not detected within 1.5 times of the previous R-R interval from the previous R peak. Both these values were chosen after some preliminary simulations. Figure 4 shows the output waveforms of these steps. From this figure, it could be seen that the algorithm has successfully identified approximate QRS segments for R peak identification.

With the detection of the QRS segment, R peak was detected as the biggest upward deflected peak in the segment. The Q point was detected as the first downward deflection trough by tracing back 50 ms from R point. Similarly, S point was detected as the first upward deflection peak by tracing forward 100 ms from R point.

Since each pattern in our signal consisted of 4 beats, we obtained the following features for the

[1] In [6], the authors used N = 30 for sampling frequency of 200 Hz. Here, we use N = 54 for sampling frequency of 360 Hz.

studied third beat: R peak amplitude normalised by the previous R peak, pre and post R-R intervals normalised by the first R-R interval, pre and post delta R-R[2] and QRS width normalised by the previous QRS width. These normalisations were done to reduce the variations across different subjects.

2.3. BP Pre-processing

Similar to ECG signals, BP signals were also pre-processed to reduce noise. The notch filter as in Eq. (1) was used to reduce 60 Hz powerline interference. Next, the BP signals were bandpass filtered from 0.5 to 15 Hz using a low-pass and high-pass Butterworth digital filter. The frequency range was chosen following the approach in [8]. These filtering reduced 60 Hz, high frequency and baseline noises. Figure 5 shows the BP signals before and after noise reduction.

2.4. BP feature extraction

The systolic (peak) and diastolic (trough) values were detected by simple peak and trough detection methods. The pre and post SBP and DBP values were used to compute the change in SBP and DBP values, i.e. delta SBP and delta DBP.

These two features were combined with the 6 features from ECG signal to give a total of 8 features.

2.5. MLP-BP neural network

MLP neural network trained by the BP algorithm was used to classify the computed features into either normal, PSC or PVC categories. Half of the data (375 patterns) were used to train the network while the rest half (375 patterns) were used in testing. The hidden nodes were varied from 5 to 25 nodes in steps of 5. The input layer consisted of 8 nodes because the number of features was 8, while the output layer was set to 3 nodes for the three classes. The target output for the trained pattern was set to 1.0, while for the rest of the classes, it was set to 0. Training was conducted until the average error falls below 0.01 or the maximum iteration limit of 1000 is reached. Figure 6 shows the architecture of the MLP-BP network architecture as used in this study.

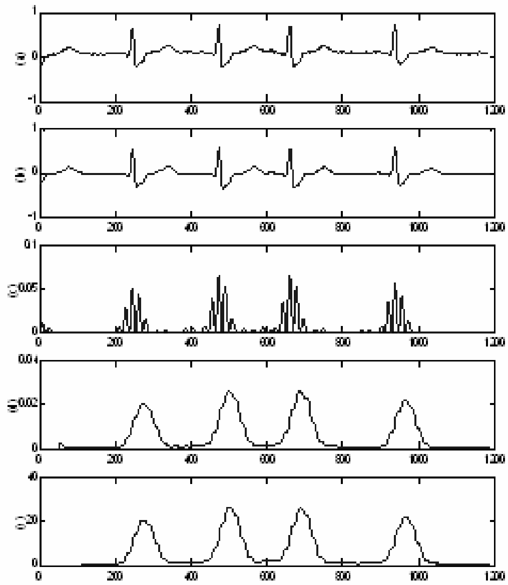

Fig. 4 Output waveform for the steps to extract QRS segment (a) Original ECG signal (b) After noise reduction (c) After bandpass and squaring (d) After moving average integration (e) After shifting for filtering delay

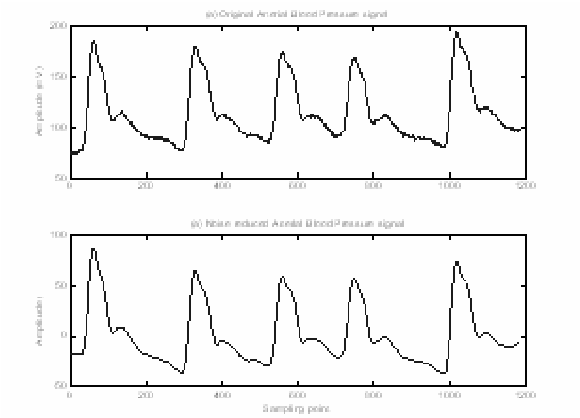

Fig. 5 BP signals (a) original (b) after reducing noise

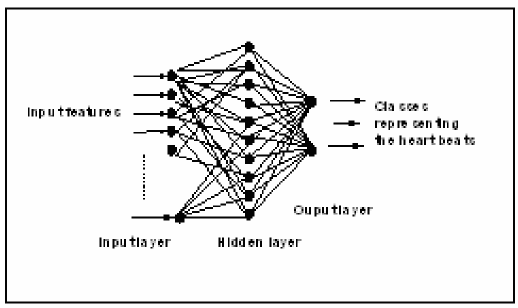

Fig. 6 MLP-BP network architecture

[2] Delta R-R was measured as the change of current R-R interval with the first R-R interval.

3. RESULTS

Table 1 shows the MLP-BP classification results for the varying hidden units. The table also lists the number of patterns that failed for each class.

Table 1: MLP-BP Classification results

	Classification		No. of failed patterns		
Hidden units		**(%)**	**Normal**	**PSC**	**PVC**
5	**342/375**	**91.20**	**6**	**10**	**17**
10	**344/375**	**91.73**	**7**	**9**	**15**
15	**345/375**	**92.00**	**4**	**11**	**15**
20	**342/375**	**91.20**	**4**	**9**	**20**
25	**344/375**	**91.73**	**4**	**8**	**19**
Average	**343.4/375**	**91.57**	**5**	**9.4**	**17.2**

4. DISCUSSION

As could be seen from Table 1, the performances did not vary much with different hidden modes. The best performance of 92% was achieved for 15 hidden nodes. Therefore, in future works, number of hidden nodes as small as 10 or 15 could be used for this type of heart beat classification. The number of failed patterns was highest for PVC, followed by PSC and normal. This is not surprising considering the QRS waves exhibited by PVC are bizarre. The QRS waves shown by PSC are less bizarre than PVC but more bizarre than QRS waves shown by normal beats.

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.

5. CONCLUSION

In this work, we have extracted features extracted from lead I ECG and arterial BP signals to detect PSC and PVC, two commonly encountered ectopic beats. Previous studies have used only ECG signals for this purpose. The inclusion of BP features for detection is warranted by the fact that occurrences of these beats would result in variations in BP waveforms. The classification of normal, PSC and PVC beats gave detection accuracies up to 92%. It may be possible to increase the detection accuracy by including other leads and other BP signals like Central Venous Pressure. 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 threatening arrhythmias and this may help to save lives.

6. REFERENCES

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