# ABP Peak Detection using Energy Analysis Technique

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***Abstract— This paper describes an algorithm for the automatic detection of systolic peaks in the Arterial Blood Pressure (ABP) signal. ABP waveform is rich in pathological information such as heart rate, systolic, mean and diastolic pressure therefore it is very important for clinical diagnosis in cardiology. The proposed algorithm deals with the development of energy based technique for the detection of systolic peaks in ABP signal that is of great importance in evaluating heart rate computation and serves as the basis for the extraction of other ABP features. The algorithm has been developed based on the window based energy analysis of ABP signal. This energy domain offers an easy interpretation of the ABP signal for the detection of systolic peaks in ABP signal. The ABP signal under test undergoes window based energy analysis by selecting a window of 100 ms duration. The window is shifted along time axis and the energy of samples falling in the succeeding window is calculated. The areas in ABP signal where systolic peaks are available appear as high energy zones. Window based amplitude threshold and interval threshold are applied to reject the unwanted peaks. The algorithm is easier to implement just after removal of the low frequency samples in ABP signal. ABP signals are downloaded from MGH/MF waveform database and algorithm has been developed on five minute segment of ABP signals. The method has been validated based on beat annotations of five minute segment of corresponding ECG signal from modified lead II.***

## I. INTRODUCTION

ABP waveform comprises of valuable information about cardiovascular function. Blood pressure waveform analysis has been used for the assessment the properties of arterial vessel wall [1], cardiac output monitoring [2], estimating pressure pulse index [3], cardiac arrhythmias detection [4]. Therefore, it is apparent that analysis of ABP waveform can depict better insight of cardiac physiology. The features of ABP signals are systolic pressure, diastolic pressures and dicrotic notch. Some times conditions may arise when ECG signals may be completely corrupted by intensive electrical noise or ECG signals may not be available due to surgical dressing of patients. An alternative solution to this issue is blood pressure waveform since noise on the blood pressure waveform is not correlated with the noise on the ECG. Noise on the pressure signal is commonly mechanical in nature, whereas electrical noise interferes more with the ECG. Characteristics of the ABP waveform such as systolic peak and the dicrotic notch, can therefore be used to evaluate heart rate when the ECG is excessively noisy.

Algorithm developed by M. Aboy [5] includes peak detection of two ABP signals from CSL database. The algorithm utilizes a filter bank with variable cutoff frequencies, spectral estimates of the heart rate, rank-order nonlinear filters, and decision logic. The algorithm developed by Navakatikyan etal [6] is based on the continuous independent assessment of the refractory period (RP). Li etal [7] proposed an automatic delineator for the detection of fiducial points of arterial blood pressure waveforms, namely their onsets, systolic peaks and dicrotic notches. It firstly seeks the pairs of inflection and zero-crossing points, and then utilizes combinatorial amplitude and interval criteria to select the onset and systolic peak. The delineator is based on the combinatorial analysis of arterial blood pressure waveforms and their derivatives. Most of the recorded ABP signals suffer from instrumental unreliability and measuring inconsistency. Secondly, their validation and performance evaluation is based on small datasets, which were from selected patients and with limited number of beats only [5]. In particular, it is difficult to evaluate those systems and algorithms by their proprietary datasets. It is therefore essential to develop an algorithm on open databases, validated as modern ECG algorithms, includes performance, generality and robustness against physiological interferences.

We suggest an energy based technique to detect the systolic peak captured from cardiac electrical signatures in the form of ABP waveform. The algorithm has been developed on an open access MGH/MF waveform database [8]. The developed algorithm is validated with reference ECG annotations on MGH/MF database to account for number of beats in each signal.

## II. MATERIALS

### *A. Signal Energy*

Signals in time domain with different amplitudes over a different period of time may possess equal strength since they

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carry equal energies. In general, signal energy is defined as the area under the curve. Signal energy is calculated by squaring the signal or taking its absolute value. Samples with negative amplitude equally contribute to the energy calculation as the samples with positive amplitude. Bio-generated signals are disrupted on their way by some resistance of the nerves etc. Due to this reason, the amplitude gets lowered but the area remains the same or may be larger. Therefore, energy analysis of biomedical signals provides an excellent method for the analysis of some features of the signal [9].

For any continuous time signal x(t), the quantity

$$E = \int_a^b |x(t)|^2 \, dt \tag{1}$$

is called the energy in the signal *x(t)* over the time interval $a \le t \le b$ [10].

Similarly, for a discrete time signal, *x[n],* the total energy is given by-

$$E = \sum_{n=n1}^{n2} |x[n]|^2 \tag{2}$$

### *B. MGH/MF Waveform Database*

In order to evaluate the detector performance, It is necessary to acquire the signals from some standard database so that the obtained results may be interpreted with respect to that open access database. The ABP signals under analysis are acquired from MGH/MF waveform database. The signals in the database are sampled at 360 samples/second. Each record consists of .dat file, .hea file, .ari file and comprises of 8 signals. ECG lead II and ABP signals of record mgh001 are considered for the analysis.

The signals in record mgh001 from MGH/MF waveform database are described table 1.

## III. METHOD OF DETECTION

The signals from MGH/MF waveform database are not readable by MATLAB directly. These signals are converted into .mat files. The resultant .mat file comprises of 8 signals as mentioned in table 1. The extracted signals are then separated to read each signal individually. Then the signals are converted from raw units to physical units.

TABLE I. DESCRIPTION OF RECORD MGH001 OF MGH/MF WAVEFORM DATABASE

| Record | Signal | Gain | Base | Units |
|---|---|---|---|---|
| Mgh001 | ECG lead I | 1167 | -127 | mV |
| | ECG lead II | 1208 | -573 | mV |
| | ECG lead V | 1121 | -1070 | mV |
| | ART | 12.06 | -1215 | mmHg |
| | PAP | 20.72 | -1015 | mmHg |
| | CVP | 20.08 | -1006 | mmHg |
| | Resp. Imp. | 1000 | 0 | mV |
| | $CO_2$ | 1000 | 0 | mV |

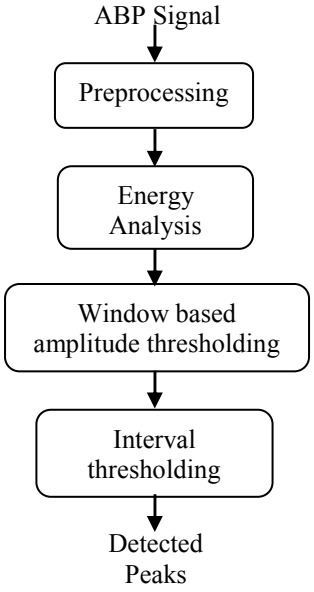


FIG 1. BLOCK DIAGRAM OF PEAK DETECTION ALGORITHM

Finally, the signal segments for five minute duration when both ABP and ECG II signals are available are considered for analysis.

### *A. Preprocessing*

Variations in signal amplitude may result in the erroneous calculation of energy. The biomedical signals are corrupted by artifacts such as base line drift, power line interference etc. Base line drift causes sharp variation in signal amplitude. That is why, removal of low frequency artifacts is the key step before starting the detection process by this method. Pressure signals have frequency range from 0.7-3.5 Hz [5]. The signal under test is filtered by fourth order butterworth highpass filter with cutoff frequency of 0.5 Hz to eliminate low frequency artifacts.

### *B. Energy Analysis*

The filtered signal then undergoes energy analysis by windowing technique considering a window of 100 ms. This method of energy calculation requires zero padding to the signal to calculate the energy of samples falling in the last window. Therefore, half the number of samples required to add are added to the beginning and end of the signal. The length (L) of new signal is given by-

$$L = \frac{b}{2} + N + \frac{b}{2} \tag{3}$$

Where, '*N*' denotes the total number of samples in ABP signal before zero padding and *'b'* is number of samples in the window.

The number of samples can be distributed to each window as follows -

$$N = n_1, n_2, n_3 \ldots\ldots\ldots\ldots\ldots n_n \tag{4}$$

Where,

$n_1 = a : b$

$n_2 = (a+1) : (b+1)$

$n_3 = (a+2) : (b+2)$.....

$n_n = [\{(a+(N-1))\} : \{(b+(N-1))\}]$

Here 'a' refers to beginning of window and $n_1, n_2, n_3 \ldots\ldots n_n$ consists of the first to last sample numbers of corresponding window.

The generated energy signal has the length equivalent to the length of ABP signal. The energy distribution of ABP signal under test using a window of 100 ms duration is shown in figure 2. Scaling is done to the amplitude of ABP signal for better illustration of the fact that energy is higher where systolic peaks are available.

*C. Window Based Thresholding*

The energy signal now undergoes window based thresholding to eliminate unwanted peaks. This method of thresholding adds to the adaptive threshold to overcome any large variations in the signal amplitude due to which the true peaks with lower amplitudes may be ignored.

Let the signal length be L that has to undergo window based thresholding. The total number of samples in the signal is divided by the window size and the remaining samples are discarded. If the signal in the sample form is defined as

$$y = u : v$$

Where, *u=1* denotes the first sample no of the signal and '$v$' is the last sample of the signal. Let '$w$' be window size then the new signal ($y_1$) in sample form can now be represented as

$$y_1 = u : (v - R)$$

Where, *R* is the remainder achieved after dividing the last sample no. $(v)$ by window size $(w)$.

The total number of windows in the signal be *M*, then

$$M = \frac{v-R}{w}$$

The new signal is represented as the segments of window size. Let the total number of windows in the sample be *N*, then we can write

$y_1 = (u : w), ([(w+1) : 2w]), ([(2w+1) : 3w])$.....

.....$([(M-1)(w+1) : Mw])$

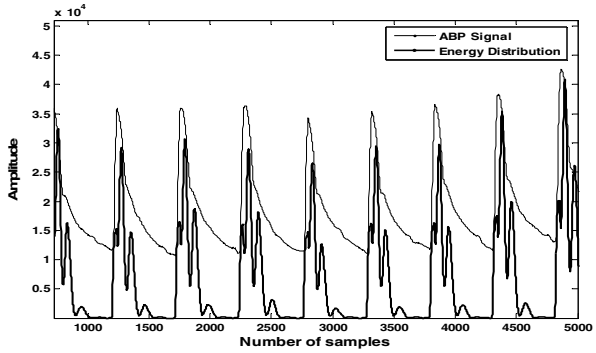


FIG 2. ABP SIGNAL AND ITS ENERGY DISTRIBUTION

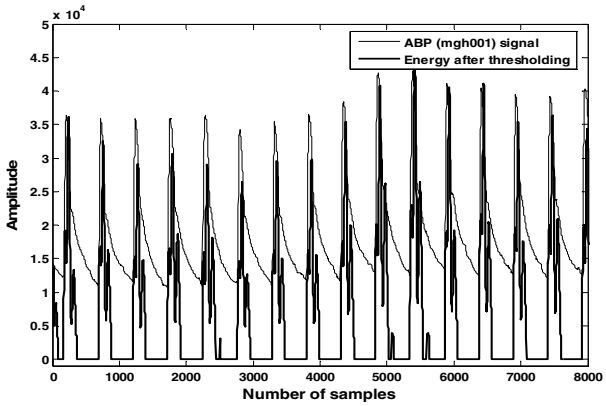


FIG 3. ABP SIGNAL AND THRESHOLDED ENERGY SAMPLES

Let $th_1, th_2, th_3 \ldots\ldots th_n$ be the threshold for each window, then

$$th_1 = A \times [\max(y_1(u : w))]$$

Where, *A* is the percentage that is fixed for overall process.

ABP signal under test and its energy signal after window based thresholding using a window of 2 sec duration is shown in figure 3. The energy samples below the pre-defined threshold are set to zero. Out of these energy thresholded samples, those samples are taken in to account which possess highest energy between two zeros.

The onset or offset samples of remaining thresholded energy windows provide an idea of approximate number of peaks available in the signal and their positions are assumed as possible systolic peaks. ABP signal is also derived from cardiac signatures like ECG signal. Assuming this fact an interval threshold of 200 ms duration is applied after detection of first peak in ABP signal under test. As no two consecutive peaks can be found during less than 200 ms, a window equivalent to 200 ms is skipped in the signal after detection of first peak which further helps in eliminating the false peaks detected as systolic peaks after application of window based amplitude thresholding [11].

## IV. RESULTS

There are several databases on the physionet namely fantasia database, MIT-BIH Polysmographic database and MGH/MF waveform database etc. but the pressure signals are not annotated so far in any database. Both ABP and ECG signals are available for the same duration and from the same patient in MGH/MF waveform database. ECG signals in the database are annotated by experts [8]. Also, it has been observed that any abnormality in ECG waveform at particular instant is also available in ABP signal so the approved ECG annotations can help to evaluate the detector's performance [14].

Li etal [7] evaluated the performance of their algorithm on Fantasia database [12] and Polysmographic (SLP) database [13]. Fantasia database consists of non-invasive ABP waveform along with synchronously sampled ECG recording

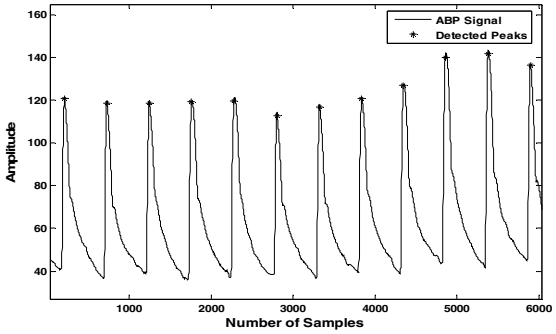


FIG 4. ABP SIGNAL WITH POSITIONED SYSTOLIC PEAKS

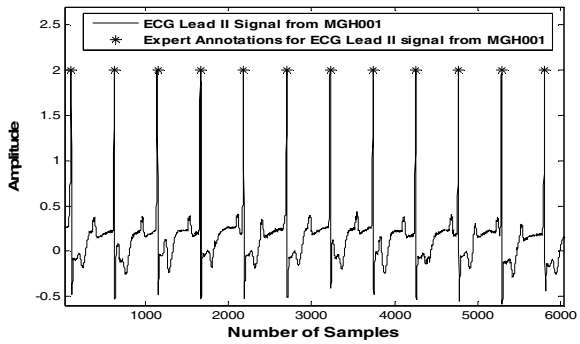


FIG 5. ECG SIGNAL WITH POSITIONED PEAKS

with approved beat annotations. On the contrary, SLP database is the collection of invasive ABP signals as well as synchronously sampled ECG recordings with approved beat annotations. So far evaluation of beat detection algorithm on MGH/MF waveform database is not reported. Li etal [7] employed the strategy if ABP waveform is clear and corresponding ECG annotation is available, the beat annotation is considered as TP or FN based on its presence or absence. Otherwise the beat annotation is considered as FP if there is no clear ABP waveform or ECG annotation. W Zong etal [14] also employed the same strategy for the performance evaluation of their algorithm based on ECG annotations. We suggest the same method for performance evaluation for our algorithm by considering equal segments of both ABP and ECG recordings.

The number of actual beats is counted from expert annotations for ECG signal of same duration as the ABP signal under test and beats positions are validated manually. The algorithm has been tested on the first nine records of MGH/MF waveform database. The algorithm achieved an accuracy of 99.53% for ABP signal of mgh001 record whereas the overall accuracy of detection is 98.05%. Out of total 4121 beats 4043 beats were correctly detected. The algorithm reported 78 peaks missing whereas 01 peak is detected as false beat. In addition to accuracy, two other measures of detector's performance such as sensitivity and positive predictivity are also studied. The algorithm reported sensitivity of 99.98% and positive predictive value of 98.14%. The systolic peak positions have been detected and marked on the original signal. ABP waveform with the positioned systolic peaks by energy analysis technique is shown in figure 4 and corresponding ECG lead II signal with approved beat annotations is shown in figure 5. The positions are marked as '*'.

## V. CONCLUSION AND DISCUSSION

An algorithm for ABP peak detection based on energy analysis of ABP signal has been proposed. The algorithm uses window based energy analysis of ABP signal by defining a window of 100 ms duration. The use of window based amplitude threshold adds to make the method adaptive which prevents actual peaks of lower amplitude being missed after thresholding. This energy based approach for ABP peak detection can be used with ECG algorithm to identify ectopic beats which are life threatening [4]. The algorithm is very straightforward to execute just after the removal of low frequency samples. This method clearly identifies the higher energy zones in the generated energy signal where peaks exist in the corresponding locations in the ABP signal.

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