Automatic Detection Algorithm for Physiologic Pressure Signal Components

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Abstract- **This paper describes an offline detection algorithm for pressure signals that incorporates heart rate, amplitude, and interbeat intervals to identify the time location of four signal components. The algorithm performance was assessed based on the statistics of the interbeat intervals of the detected componets. The algorithm performed well when applied to arterial blood pressure and intracranial pressure signals acquired from patients in a pediatric intensive care unit.**

Keywords – **Pressure detection, QRS detection, beat detection.**

I. INTRODUCTION

Detection algorithms of signal components are important tools for beat-level physiologic signal analysis and automatic diagnosis. Although many QRS detection algorithms for electrocardiograms have been proposed [1], there are only a few publications that describe algorithms that detect signal components of pressure signals such as intracranial pressure (ICP) and arterial blood pressure (ABP) [2]. The structure of QRS detection algorithms generally consists of a preprocessing stage that emphasizes the signal components of interest and a decision stage for identification, similar to the structure shown in Fig. 1. Many of the techniques used in QRS detection that take advantage of the impulsive shape of the QRS complex do not work well on pressure signals that lack this.

We describe an automatic algorithm for the detection of components in physiologic pressure signals that is robust to noise and time-varying morphology of the cardiac component. The algorithm incorporates the estimated heart rate, component amplitude, and interbeat intervals to accurately and automatically detect the components shown in Fig.2.

II. ALGORITHM DESCRIPTION

The algorithm can be divided into two stages as shown in Fig. 1. The purpose of the preprocessing stage is to emphasize the pressure signal components and to filter out noise and artifact in the raw signal. The decision stage includes the peak detection and the decision logic used to classify the different components.

1) *Maxima/Minima Detection and Digital Filtering*: The algorithm detects all the maxima and minima in the raw data before applying any filtering to the pressure signal. These are used in Step 4. Given the pressure signal time-series $x(n)=(x_1, x_2, ..., x_N)$, the maxima and minima are all the points that meet the following criteria, respectively.

$$Xmax = x(n) : x(n-1) < x(n) > x(n+1) \quad (1)$$

$$Xmin = x(n) : x(n-1) > x(n) < x(n+1) \quad (2)$$

Next, a high-pass filter with a cutoff frequency of 0.5 Hz is used to eliminate the signal trend. A lowpass filter with cutoff frequency equal 10 Hz is then used to smooth the signal.

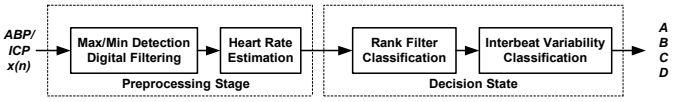

Fig. 1. Block diagram showing the architecture of the detection algorithm for pressure waveform components.

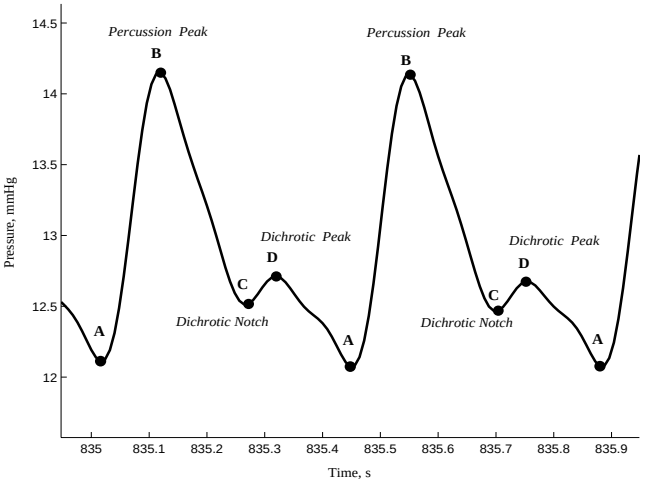

Fig. 2. Example of the waveform components for an intracranial pressure signal versus time. The same components occur in ABP signals. The B component corresponds to the percussion peak, the C component to the dichrotic notch, and the D component to the dichrotic peak.

The filters are applied forward and backward to eliminate any phase shift. Combined, these operations effectively bandpass filter the signal with zero phase delay.

2) *Heart Rate Estimation*: The filtered signal is divided into non-overlapping 10 s windows and the heart rate is estimated within each window using the power spectral density (PSD) estimated by the modified periodogram [3]. The heart rate of each window is defined here as the frequency component with largest magnitude in the interval 0.5 to 4 Hz. The average interbeat interval (T) is estimated as the median of the inverse heart rates estimated from each of the 10 s windows. The median is used to ensure the estimated T is not significantly affected by large artifact in a fraction of the windows.

$$T = \text{median}\ \{1/f_1, 1/f_2, ..., 1/f_w\}, \quad W = 10 f_s \quad (3)$$

3) *Rank Filter Classification*: This step coarsely estimates the A and B components using the maxima and minima in the detrended and smoothed signal. The detector uses a rank-based filter with a running window of length 10 s. Minima below the 20^{th} percentile are classified as A components and the maxima above the 70^{th} percentile are classified as B-components.

$$A = Xmin: x(n) < 20^{th} \text{ percentile in } W_i,\ i = 1, 2, ..., N/10 f_s \quad (4)$$

$$B = Xmax: x(n) > 70^{th} \text{ percentile in } W_i,\ i = 1, 2, ..., N/10 f_s \quad (5)$$

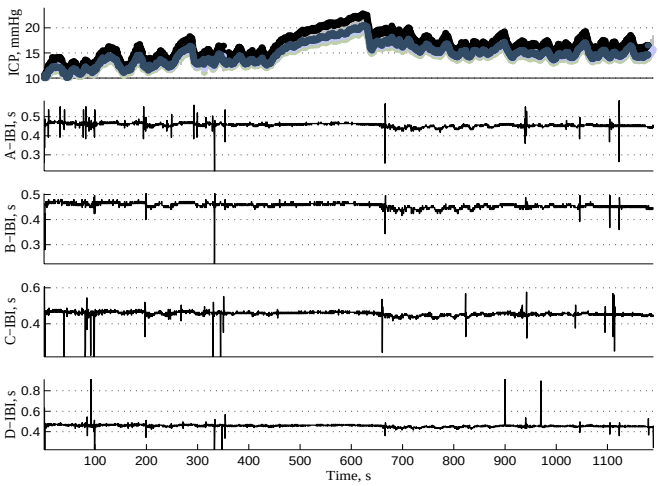

Fig. 3. Plot of a 20 min. segment of an ICP signal and the interbeat intervals of each of the four components (A,B,C, and D).

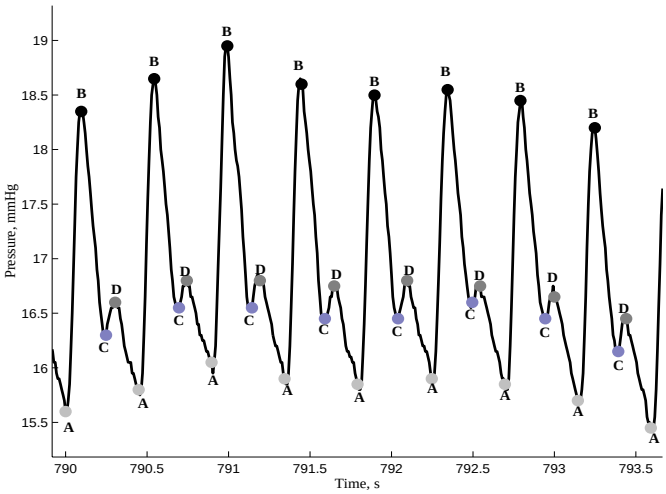

Fig. 4. Segment of the ICP signal and detected components.

4) *Interbeat Variability Classification*: Two time series containing the interbeat intervals between the location of the detected components are generated for *A* and *B*, respectively. Using the estimated average interbeat interval (*T*), the algorithm recursively searches the time series for the first instance where the interbeat distance is lower than *T/2*. This is considered a false positive so the component is removed, the time series is reconstructed, and the search is repeated until all of the false positives have been removed. The time series is then searched for cases where the interbeat distance is greater than *2T*, which is considered a missed detection. To correct this problem, the algorithm recursively searches the initial maxima and minima time series obtained in Step 1 and adds the component that minimizes the interbeat variability. This process is repeated until all of the A and B components are detected.

The algorithm classifies the remaining minima and maxima from the filtered signal as C and D components. The same process for interbeat variability minimization is applied to the *C* and *D* time series.

III. Results and Discussion

The accuracy of the algorithm was evaluated based on the statistics of the interbeat interval of the detected beats and visual inspection of plots such as the one presented in Fig. 3. The algorithm performs well in the presence of noise, artifact, and the time-varying morphology found in ABP and ICP signals. We are currently in the process of validating the algorithm against manual annotations generated by physiologic signal analysis experts in order to assess the performance of this algorithm quantitatively.

Figure 3 shows a plot of a 20 min. segment of an intracranial pressure (ICP) signal after detection. The top plot shows the actual detection and the four plots below it show the interbeat interval time series for the A, B, C, and D components. The ICP signal was acquired at the Pediatric Intensive Care Unit of the Doernbecher Children's Hospital (Oregon Health & Science University). It was sampled at 125 Hz and therefore all the interbeat intervals are approximately 0.5 s, the normal period for children.

In this patient population, a significant increase in the interbeat interval usually indicates a missed detection (false negative) and a significant decrease indicates a false positive. It can be seen from Fig. 3 that the B component (percussion peak) contains the fewest detection errors. The A and B components are always present, but C and D may disappear for a period of time and reappear some time later in the ICP signal. Special care must be taken to account for these situations where the period is genuinely greater than twice the estimated period. Fig. 4. shows a segment of the ICP signal to more clearly illustrate the detected components.

IV. Conclusion

In this paper, we described an offline algorithm that automatically detects the waveform components in physiologic pressure signals. This type of algorithm is important for beat-level signal analysis and processing. The algorithm incorporates information about the heart rate, amplitude, and interbeat intervals to identify the time location of the different components. The algorithm performs especially well on pediatric populations who rarely have premature ventricular contractions (PVC). We are in the process of quantitatively validating the algorithm on ABP and ICP signals acquired from this patient population.

References

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