Detecting Heartbeats in the Ballistocardiogram with Clustering

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Abstract

A method for the precise detection of heartbeats from a ballistocardiography (BCG) signal is presented. First, feature vectors are extracted from the signal at possible heartbeat positions. Complete-link clustering is then applied to the vectors to find a cluster with the highest density. The densest cluster corresponds to the most accurately repeating shape in the signal and thus the positions of the feature vectors of the densest cluster should match real heartbeat positions in the signal. The method was tested with over five hours of BCG recordings and out of the total 19375 heartbeats 49.20 % were found using the method such that 0.09 % of the heartbeats were incorrectly positioned.

1. Introduction

The heart rate of a patient can be estimated by measuring and analyzing the vibrations of the body. A convenient way to measure cardiac activity in a hospital setting is to use a contactless method, such as ballistocardiography (BCG) (Weissler, 1974), that can measure the vibrations without any disturbances to the patient.

The convenience of contactless measurements does not come without a cost as the vibration signals contain various artefacts. In the case of BCG, the sensor supports a part of the patient's body and thus also registers body movements other than cardiac activity.

A variety of signal analysis methods have been developed for detecting the heart rate from signals produced by contactless measurement devices. Existing methods are based, for example, on bandpass filtering (Brink et al., 2006), use of specific wavelet scales (Chen et al., 2008), detecting specific shapes (Smrcka et al., 2005; Xu et al., 1996) or analyzing the frequency content of the signal (Masloboev et al., 2004). The methods detect heart rate well in ideal conditions when artefacts are few, but may report an incorrect heart rate when the signal contains movements artefacts.

We present a method for the precise detection of heartbeat locations from a BCG signal that should be able to perform with few errors even if the signal contains movement artefacts. The goal of the method is not to detect all the heartbeats including those obscured by artefacts, but to avoid detecting any artefacts as heartbeats, which is a problem that many existing methods have.

The methods were developed and implemented using the SciPy scientific computing package (Jones et al., 2001), with hcluster (Eads, 2008) used for hierarchical clustering.

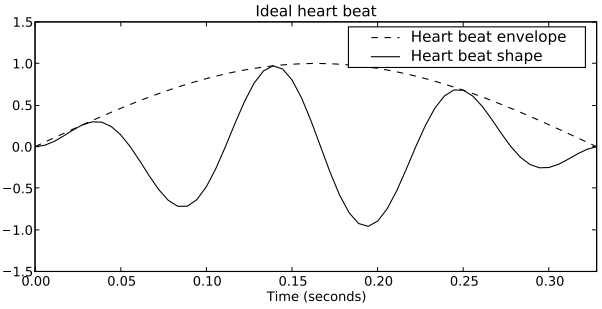

Figure 1. An ideal heartbeat with $f_b = 9$ Hz and $d = 0.33$ seconds.

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2. An Ideal Heartbeat Signal Model

We present an ideal BCG heartbeat signal model

$$x(t) = w(t) * y(t) + \eta \tag{1}$$

that consist of a convolution of a heartbeat shape $w(t)$ and heartbeat train $y(t)$ as well as stationary additive noise η. The heartbeat shape

$$w(t) = \begin{cases} \sin\left(\frac{\pi t}{d}\right) sin(2\pi f_b t) & \text{if } 0 < t < d \\ 0 & \text{elsewhere} \end{cases} \tag{2}$$

of the model is a sinusoid with frequency f_b windowed with a cosine window whose width is d (Figure 1). The heartbeat train

$$y(t) = \sum_{k=1}^{M} a_k \delta(t - t_k) \tag{3}$$

consists of zeros except at the heartbeat locations t_k where its value is a_k, representing the amplitude of the heartbeat occurring at t_k. The heartbeat occurrence times t_k have the restriction

$$\min(t_{k+1} - t_k) > d \tag{4}$$

that the time between any two heartbeats must be more than d. Heartbeat amplitudes a_k are constrained so that the greatest heartbeat amplitude must be less than r times the smallest heartbeat amplitude and that all amplitudes must be positive,

$$\max(a_k)/\min(a_k) < r \tag{5}$$

$$\min(a_k) > 0. \tag{6}$$

In words, the ideal heartbeat signal can be described in the following way:

1. The shape of every heartbeat is equal, but their amplitudes vary
2. The greatest heartbeat amplitude is at most r times the smallest amplitude
3. The heartbeat shape envelope has a bell-like form
4. The delay between two consecutive heartbeats is at least d
5. The duration of a single heartbeat is d
6. The signal contains additive noise

By choosing values such as $d = 0.33$ seconds, $f_b = 9$ Hz and $r = 3$ for the parameters, the ideal heartbeat signal model represents a BCG signal quite well. A simulated ideal heartbeat signal is shown in Figure 2 and a real BCG signal in Figure 3.

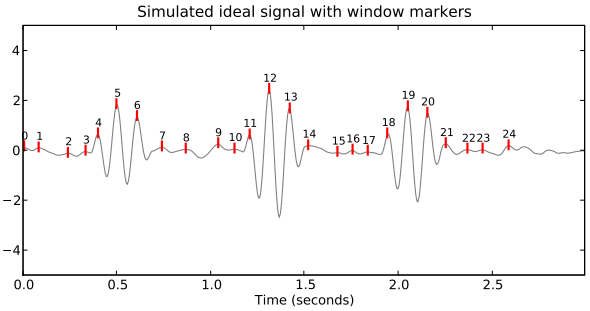

Figure 2. A simulated segment of an ideal heartbeat signal. η (see Eq. 1) is lowpass-filtered (40Hz cut-off) gaussian noise, producing a signal-to-noise ratio 3 for the signal. Positions p_i where the feature vectors $\mathbf{q_i}$ begin are shown as vertibal bars, with i shown above the bar.

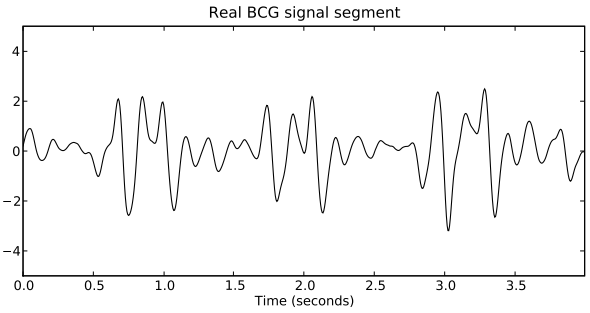

Figure 3. A pre-processed BCG signal with three heartbeat occurrences. The signal was first lowpass-filtered with 20 Hz cut-off, after which a discrete difference was taken.

3. Locating Heartbeats

We present a method for locating heartbeats from signals that resemble the ideal heart signal presented above.

First, a set of possible heartbeat positions p_i is determined as the local maxima of $x(t)$, which are the positions where a falling zero crossing of the difference of $x(t)$ is detected, that is, both (7) and (8) hold.

$$\Delta x(p_i) > 0 \tag{7}$$

$$\Delta x(p_i + 1) \leq 0 \tag{8}$$

The positions p_i for a simulated ideal signal are shown in Figure 2. For every position p_i, the feature vector

$$\mathbf{q_i} = \begin{bmatrix} x(p_i) \\ x(p_i + 1M) \\ x(p_i + 2M) \\ \vdots \\ x(p_i + (n-1)M) \end{bmatrix} \tag{9}$$

contains n every M samples of $x(t)$ starting at $x(p_i)$. Our signals were sampled at $f_s = 180$ Hz and lowpass-filtered with a 20 Hz cutoff so it was natural to choose $M = 4$, which enables the downsampled signal to contain frequencies up to 22.5 Hz. With $n = 30$, the temporal length of the feature vectors became $(n * M)/f_s = (15 * 4)/180\ \mathrm{s}^{-1} = 0.66$ s, which was considered to be a suitable size as it corresponds the beat-to-beat interval of 90 bpm, which is a somewhat mid-range heart rate.

The dissimilarity function

$$d(\mathbf{q_i}, \mathbf{q_j}) = \begin{cases} \cos^{-1}\left(\frac{\mathbf{q_i} \cdot \mathbf{q_j}}{\|\mathbf{q_i}\|\|\mathbf{q_j}\|}\right) & \text{if } \frac{1}{\hat{r}} < \frac{\|\mathbf{q_i}\|}{\|\mathbf{q_j}\|} < \hat{r} \\ & \text{and } \|p_i - p_j\| > \hat{d} \\ \pi & \text{otherwise} \end{cases} \tag{10}$$

is based on calculating the angle between feature vectors. Angular dissimilarity is used, because it ignores differences in feature vector amplitudes. Parameters $\hat{r} = 3$ and $\hat{d} = 0.33$ s are suitable for BCG signals, and allow a maximum heart rate of 180 bpm.

A standard dissimilarity matrix

$$P = \begin{pmatrix} 0 & d(\mathbf{q_0}, \mathbf{q_1}) & \cdots & d(\mathbf{q_0}, \mathbf{q_{n-1}}) \\ d(\mathbf{q_1}, \mathbf{q_0}) & 0 & \cdots & d(\mathbf{q_1}, \mathbf{q_{n-1}}) \\ \vdots & \vdots & \ddots & \vdots \\ d(\mathbf{q_{n-1}}, \mathbf{q_0}) & d(\mathbf{q_{n-1}}, \mathbf{q_1}) & \cdots & 0 \end{pmatrix} \tag{11}$$

was used in performing complete-link hierarchical clustering (Theodoridis & Koutroumbas, 2006). At each step i of the hierarchical clustering procedure, dissimilarity d_i, size s_i and the created cluster C_i are available. Those three data are processed with Algorithm 1 to find the most optimal cluster.

The criteria for the most optimal cluster are that it should have as large a cluster density s_i/d_i as possible and that the distance d_i should not exceed $\pi/4$, which was chosen after experimentation with different values. The limit is used, because the current density measure assigns a too large density to large, relatively sparse clusters. After a better measure for cluster density has been developed, the limit can be removed.

Algorithm 1 Finding the optimal heartbeat cluster

Input: dissimilarities d_i, sizes s_i, clusters C_i
Initialize $i = 1$.
Initialize $clusterDensity = 0$.
repeat
  if $s_i/d_i > clusterDensity$ **then**
    $resultCluster = C_i$
    $clusterDensity = s_i/d_i$
  end if
  $i = i + 1$.
until $d_i > \frac{\pi}{4}$
return $resultCluster$

4. Results

The method for locating heartbeats was tested with both simulated and real signals.

4.1. Simulated Signals

Figure 4 shows a dendrogram based on clustering the signal segment of Figure 2. The first cluster that reaches three items ($\mathbf{q_5}, \mathbf{q_{12}}, \mathbf{q_{19}}$) represents feature vectors (Figure 5) that are extracted from the same part of the three heartbeat shapes of the signal. Also the next two three-item clusters (($\mathbf{q_6}, \mathbf{q_{13}}, \mathbf{q_{20}}$), ($\mathbf{q_4}, \mathbf{q_{11}}, \mathbf{q_{18}}$)) represent heartbeats.

As the clusters representing heartbeats are formed first in the dendrogram, complete-link clustering can be used in finding the set of feature vectors that match the positions of real heartbeats in the signal.

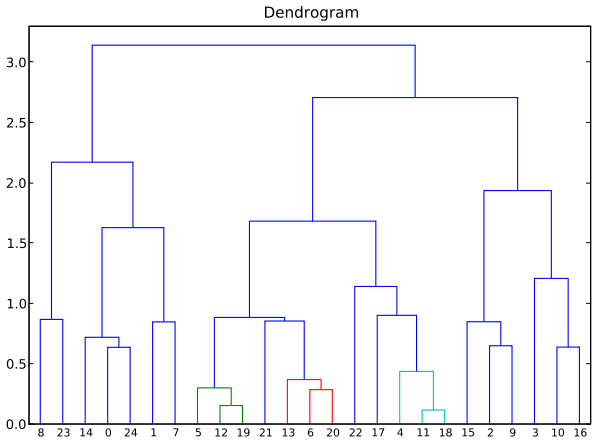

Figure 4. Dendrogram of the clustering process of the feature vectors extracted from the signal in Figure 2.

4.2. Recorded BCG Signals

In total 330 minutes of BCG signals were recorded from test subjects weighing 50, 75 and 102 kilograms with a piezoelectric pressure sensor (Ruotoistenmäki, 2005). Sampling rate was 180 Hz. Along with BCG, the electrocardiogram (ECG) was recorded for evaluation purposes. The sensor was installed so that it supported the section of a mattress that was under the patient's upper body, thus registering cardiac activity

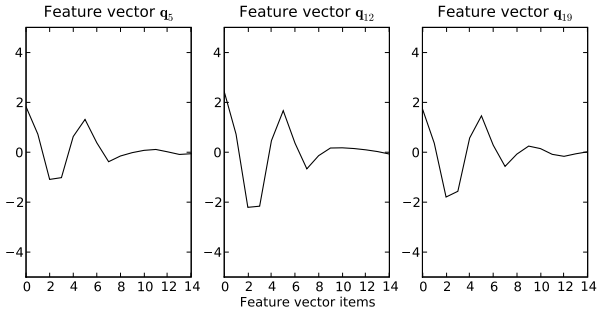

Figure 5. The most compact cluster with three members ($\mathbf{q_5}, \mathbf{q_{12}}, \mathbf{q_{19}}$).

well.

The signal was preprocessed by applying a digital finite impulse response (FIR) low-pass filter with 20 Hz cutoff frequency and calculating the discrete difference of the signal. The difference is calculated to highlight the high-frequency heart rate activity in the signal.

Test subjects were mostly lying still during recordings, but small movements caused occasional artefacts to the signal. Based on the ECG reference, the signals contained in total 19375 heartbeats. Applying our method to 20-second signal segments, 9533 heartbeats were detected (49.20 % of all heartbeats) of which 9524 (99.91 %) were correct and 9 (0.09 %) incorrect based on the ECG reference. Correctness of a heartbeat location was determined by checking if it was less than 0.05 seconds apart from an ECG heartbeat.

5. Conclusions

We have presented a method for detecting heartbeat locations from a BCG signal that is based on complete-link clustering. The method detected heartbeat locations accurately from 330 minutes of test signals, with only 0.09 % of detected heartbeat locations being incorrect.

Based on the results, clustering can be used to detect heartbeat locations very effectively, but there is still room for improvement especially in determining criteria for choosing the right cluster to represent heartbeats.

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References

Brink, M., Müller, C. H., & Schierz, C. (2006). Contact-free measurement of heart rate, respiration rate, and body movements during sleep. *Behavior Research Methods*, *38*, 511–521.

Chen, W., Zhu, X., Nemoto, T., Kitamura, K., Sugitani, K., & Wei, D. (2008). Unconstrained monitoring of long-term heart and breath rates during sleep. *Physiological Measurement*, *29*, N1–N10.

Eads, D. (2008). hcluster: Hierarchical Clustering for Scipy.

Jones, E., Oliphant, T., Peterson, P., et al. (2001). *Scipy: Open source scientific tools for python*.

Masloboev, Okhritskii, Prilutskii, & Selishchev (2004). A monitor of biomechanical cardiac activity. *Biomedical Engineering*, *38*, 165–169.

Ruotoistenmäki, H. (2005). Force or pressure sensor and the use of the same. European patent 1,563,268.

Smrcka, P., Jirina, M., Trefny, Z., & Hana, K. (2005). New methods for precise detection of systolic complexes in the signal acquired from quantitative seismocardiograph. *Intelligent Signal Processing, 2005 IEEE International Workshop on* (pp. 375–380).

Theodoridis, S., & Koutroumbas, K. (2006). *Pattern recognition*. Academic Press.

Weissler, A. M. (1974). Noninvasive cardiology; clinical cardiology monographs. *Grune & Stratton Inc., NY*.

Xu, W., Sandham, W., Fisher, A., & Conway, M. (1996). Detection of the seismocardiogram w complex based on multiscale edges. *Engineering in Medicine and Biology Society, 1996. Bridging Disciplines for Biomedicine. Proceedings of the 18th Annual International Conference of the IEEE* (pp. 1023–1024 vol.3).