Combining Multiple Methods to Improve Beat-to-Beat Interval Length Estimations in Ballistocardiograms

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Abstract

Ballistocardiography is a technique in which the mechanical activity of the heart is recorded. The locations of individual heart beats in ballistocardiograms (BCGs) can be estimated by various methods. We present a novel algorithm to obtain improved estimates of heart beat locations by merging the outputs of multiple beat-to-beat detection methods. For this purpose, the reliability of each individual estimate is assessed. A local greedy heuristic then takes these reliabilities into account to combine the individual estimates. By combining three methods instead of using a single method, the beat-to-beat interval error was reduced from up to 69.29 ms to 14.16 ms. False positive and false negative rates were reduced from up to 1.71% and 7.33% down to 0.13% and 0.28%, respectively.

1 Introduction

A ballistocardiograph measures the vibrations of the body which are caused by the mechanical activity of the heart. Modern BCG systems can be fully integrated into beds and are thus invisible to the patient. Hence, ballistocardiography seems to be particularly suited to unobtrusively monitor patients with heart diseases during sleep over longer periods of time.

Two classes of algorithms to determine the heart rate from BCGs are known in the literature: (a) spectral or time-domain methods which compute average heart rates over intervals which are several seconds long, for example, by evaluating the auto-correlation function of the signal [1]–[3]; and (b) beat-to-beat methods which detect individual heart beats and compute the interval length between two consecutive beats. Beat-to-beat interval information is necessary for advanced applications such as heart rate variability analysis, sleep staging, or arrhythmia detection. Current algorithms for beat-to-beat heart rate estimation from BCG signals either require expensive sensor arrays [4] or sensors which have to be attached directly to the patient’s body [5]. Other algorithms are designed to detect heart beats only under normal physiological conditions [6].

The recently proposed BEAT algorithm [7] only requires a single contact-less sensor and does not make any assumptions about the regularity of the heart beat. During a training phase, the algorithm adapts to the high inter- and intra-patient variability of the BCG signal. After training the algorithm on a short (e.g. 30 seconds long) segment of the BCG signal, a set of parameters describing the properties of an individual heart beat in the given signal is extracted.

Instead of relying on a single approach to detect heart beats in the remaining signal, three different methods are used simultaneously to locate the heart beats. This approach is based on the assumption that by combining multiple independent methods, each with different strengths and weaknesses, the robustness and accuracy of the estimation as a whole can be improved. Each method might indicate heart beats at slightly different locations. Additionally, spurious heart beats might be detected by any of the three methods, while on the other hand, some heart beats might only be detected by one or two of the methods. Hence, an algorithm to merge the disparate estimations of each individual method is necessary.

In this paper, we present a novel algorithm which efficiently merges heart beat location estimates from multiple different sources. The proposed method is based on a local greedy heuristic which takes the reliability of each individual estimate into account. While the algorithm was developed for the use in the BEAT algorithm, its concept can be adapted for other applications.

The following section gives a short description of the three methods used by the BEAT algorithm to detect heart beats in BCGs as introduced in [7]. Section 3 details the proposed algorithm to merge the estimates obtained from these three methods. We evaluate our method in Section 4. The paper concludes with Section 5.

2 Heart Beat Localization

The BEAT algorithm uses the following three methods to locate individual heart beats in the BCG signal. Each method makes use of a different parameter that is derived during the training phase.

2.1 Cross-Correlation

The training phase of the BEAT algorithm returns a representative template of the shape of a single heart beat in the given BCG signal. Further heart beats can be located by computing the cross-correlation between this prototype
signal and the remaining BCG signal. Due to the oscillating nature of the BCG signal, the cross-correlation function is also oscillating. We detect local maxima in the cross-correlation function and linearly interpolate them to obtain an upper envelope of the correlation signal. This envelope shows clear peaks at locations where the pattern described by the prototype, i.e., a heart beat, occurs. Fig. 1 shows an exemplary plot of the cross-correlation function, its upper envelope, and the indicated heart beat locations.

### 2.2 Euclidean Distance

The second method also depends on the shape of a single heart beat in the BCG. However, it uses a rough low-dimensional description of the heart beat, where only the locations and amplitudes of local extrema in the signal are considered. The shape of a single heart beat is described by concatenating the parameters shown in Fig. 2 for each of the peaks that constitute a heart beat.

Heart beat locations in the rest of the signal are detected by applying the same low-dimensional description to the remaining signal and computing the Euclidean distance between the parameters of the remaining signal and the parameters of the single heart beat. As shown in Fig. 1, the resulting distance function exhibits local minima when a signal segment is similar to the extracted heart beat pattern.

![Figure 2 Schematic showing the parameters used to describe the k-th peak in the BCG.](image)

### 2.3 Heart Valve Signal

The third method is related to an approach presented in [6]. The so-called heart valve signal is believed to be related to the closure of the heart valves during the cardiac cycle. It is computed from the BCG by first applying a band-pass filter, then squaring the resulting signal, and finally estimating an envelope by low-pass filtering.

Instead of using a fixed 20–40Hz bandpass, as proposed in [6], we apply a filter with a narrower, 4 Hz wide, passband and a tunable center frequency. During the training phase, we heuristically select a suitable center frequency to extract a clear heart valve signal. Fig. 1 shows that the maxima in the HV signal coincide with the occurrence of heart beats in the BCG.

![Figure 1 BCG segment with the corresponding plots of the cross-correlation function (Corr.) and its upper envelope (dotted line), the distance function (Dist.), and the heart valve signal (HVS). The vertical lines show the heart beat locations indicated by each of the methods.](image)

### 3 Indicator Fusion

#### 3.1 Reliability Heuristics

Each of the discussed methods produces a certain type of extremum in its output wherever a heart beat is found in the BCG signal. In order to reasonably merge these outputs, it is important to assess the reliability of the individual extrema.

Hence, we reduce each output function to a set of indicator pairs. Each indicator pair

\[ q = (t, w) \]

combines the time \( t \) at which the output function has an extremum with a reliability score \( w \) which indicates how reliable this extremum is as an indicator for a heart beat location.

Local maxima in the envelope of the cross-correlation, for example, are evaluated by means of their height relative to their two neighboring minima and maxima. The reliability of the \( i \)-th maximum is estimated as

\[ w_i^c = \frac{l_i + r_i}{2a_i} \cdot \frac{a_i}{\text{symmetry}} \cdot \frac{1}{\text{corr. coeff.}} \cdot \begin{cases} \frac{1}{2} \left( \frac{r_{i+1}}{l_{i+1}} + \frac{r_{i-1}}{l_{i-1}} \right), & \text{if } \frac{1}{2} \left( \frac{r_{i+1}}{l_{i+1}} + \frac{r_{i-1}}{l_{i-1}} \right) \leq 1 \\ 1, & \text{else} \end{cases} \]

where \( a_i \) is the amplitude of the maximum and \( l_i \) and \( r_i \) are the difference in amplitude between the left minima and the maximum and between the right minima and the maximum, respectively. The reliability scores are, per construction, normalized to the range of \([0, 1]\). Analogous to \( w^c \), reliability heuristics for minima in the distance function \( w^d \) and for maxima in the heart valve signal \( w^h \) are computed.
3.2 Merging Indicators

In the ideal case, the indicators of all methods would perfectly align for each and every heart beat. However, in real world scenarios, they slightly differ from each other as they are focusing on different features of the BCG signal. Spurious indicators and heart beats which are not detected by all of the methods further complicate the situation. The aim of the following procedure is to merge these disparate indicators. However, it is a-priori unknown which indicator corresponds to which heart beat. Hence, it is not possible to simply average all indicators corresponding to the same heart beat to obtain a robust estimate. Instead, groups of indicators which are close to each other and which therefore seem to correspond to the same heart beat are identified and merged.

The proposed method uses a greedy strategy in which each indicator selects up to one partner from each of the other indicator classes with whom it wants to be merged. For example, a distance indicator \( q^d \) wants to form a group with one cross-correlation indicator \( q^c \) and one HV signal indicator \( q^h \) that have a high reliability and that are close to its own position. Hence, possible partner indicators are selected from the interval \([t^d - 0.33s, t^d + 0.33s]\). If more than one indicator based on either criterion exists in this interval, their reliability scores are weighted by a symmetric Gaussian window function centered at \( t^d \) which decreases to (nearly) zero at the ends of the interval. The indicator with the higher weighted reliability is selected as partner for \( q^d \). In this situation, the window function provides the means to enforce a trade-off between the reliabilities of the potential partners and their distances to \( t^d \). Finally, the indicator \( q^d \) and its partners are merged to form a representative indicator pair

\[
Q^d = \left( T^d, W^d \right) = \left( t^d w^c + t^d w^c + t^h w^h, \frac{w^d + w^c + w^h}{3} \right)
\]

which is located at the weighted average of the indicators’ locations and whose reliability score is computed as the average of the reliabilities of the indicators. If \( q^d \) did not find two partners, Eq. 3 is adjusted accordingly.

This procedure is repeated for every other indicator, with correlation criterion and HV criterion indicators yielding representative indicators \( Q^c \) and \( Q^h \), respectively. Based on these representative indicators, a heart beat score \( H(t) \) is computed for every time point \( t \), where \( H(t) = 0 \) if no representative indicators are found at time \( t \), otherwise \( H(t) \) equals the sum of the reliability scores of the representative indicators located at time \( t \).

The whole process is visualized in Fig. 3. The given example also shows the intuition behind the grouping procedure. Each indicator follows a greedy strategy and selects its favored partners with no regard for the other indicators or a global optimization criterion. If all members of a group favor each other, the resulting representative indicators are identical and their representative scores, therefore, add up.

![Figure 3](image-url)

**Figure 3** Step-by-step visualization of the procedure to merge indicators. Stems with diamond-shaped markers indicate the times and the corresponding reliability scores of maxima in the envelope of the cross-correlation function. Maxima in the HF signal and minima in the cluster-distance function are indicated by stems with upward-pointing triangles and stems with downward-pointing triangles, respectively. The example shows a scenario consisting of a triplet of indicators and an additional spurious indicator.
Spurious peaks with low reliabilities, on the other hand, will also form a triplet but no other indicator will select them as partner. Hence, their heart beat scores will be significantly lower than those of triplets that selected each other consensual. Through this approach, groups of reliable indicators can be identified and merged without the need for a global optimization criterion.

The locations of heart beats can then be detected as time points where the beat score $H(t)$ exceeds a certain threshold.

## 4 Results

We evaluated the performance of the proposed method in the context of the BEAT algorithm by comparing the estimated heart beat locations and beat-to-beat interval lengths to a simultaneously recorded ECG. For each estimated interval, the absolute difference between its length and the length of the closest R-R interval was computed (interval error). Furthermore, the percentage of R peaks that were not detected (false negatives) and the percentage of spurious beats that were falsely detected (false positives) was recorded.

For the evaluation, 12.5 hours of BCG recordings containing 47456 heart beats were analyzed. The BCG signals were captured from healthy adults (9 male, 8 female, ages 20–50) using a sensor consisting of a slat in a bed frame which was instrumented by strain gauges.

First, we evaluated each of the methods presented in Section 2 separately to detect beat-to-beat interval lengths. Then, we tested combinations of two methods using our proposed algorithm. For the final experiment, all three methods were combined. Table 1 shows the results for each of these tests.

The results show that by combining multiple methods using the proposed algorithm, the overall accuracy of the estimated beat-to-beat interval lengths as well as the number of false positives and false negatives can be significantly improved. Combining two methods already provides a significant benefit over using a single method. However, the combination of all three methods provides the best overall results.

## 5 Conclusion

We presented three methods used by the BEAT algorithm to detect individual heart beats in BCGs. A novel algorithm was proposed to merge the disparate heart beat locations provided by these methods into more reliable and accurate estimates. This was achieved by first assessing the reliability of each individual estimate. Based on the resulting reliability scores, a local greedy heuristic was used to efficiently merge heart beat indicators which are in agreement with each other. The overall beat-to-beat interval error could be reduced significantly by using the proposed algorithm to combine all three methods.

### Table 1 Performance of the BEAT algorithm depending on the number of methods that were combined to propose algorithm to detect heart beats.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Int. Error (ms)</th>
<th>False Pos. (%)</th>
<th>False Neg. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dist</td>
<td>69.28</td>
<td>1.71</td>
<td>6.78</td>
</tr>
<tr>
<td>Corr</td>
<td>54.97</td>
<td>0.61</td>
<td>7.33</td>
</tr>
<tr>
<td>HV</td>
<td>31.33</td>
<td>0.24</td>
<td>2.17</td>
</tr>
<tr>
<td>Dist+Corr</td>
<td>31.28</td>
<td>0.79</td>
<td>2.34</td>
</tr>
<tr>
<td>Dist+HV</td>
<td>18.52</td>
<td>0.17</td>
<td>3.93</td>
</tr>
<tr>
<td>Corr+HV</td>
<td>16.20</td>
<td>0.11</td>
<td>0.40</td>
</tr>
<tr>
<td>Dist+Corr+HV</td>
<td>14.16</td>
<td>0.13</td>
<td>0.28</td>
</tr>
</tbody>
</table>

## 6 References