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Applying Machine Learning to Detect Individual Heart Beats in Ballistocardiograms

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***Abstract*— Ballistocardiography is a technique in which the mechanical activity of the heart is recorded. We present a novel algorithm for the detection of individual heart beats in ballistocardiograms (BCGs). In a training step, unsupervised learning techniques are used to identify the shape of a single heart beat in the BCG. The learned parameters are combined with so-called "heart valve components" to detect the occurrence of individual heart beats in the signal. A refinement step improves the accuracy of the estimated beat-to-beat interval lengths. Compared to other algorithms this new approach offers heart rate estimates on a beat-to-beat basis and is designed to cope with arrhythmias. The proposed algorithm has been evaluated in laboratory and home settings for its agreement with an ECG reference. A beat-to-beat interval error of 14.16 ms with a coverage of 96.87% was achieved. Averaged over 10 s long epochs, the mean heart rate error was 0.39 bpm.**

I. INTRODUCTION

Cardiovascular diseases are the leading cause of death worldwide [1]. One way to better prevent and manage cardiac diseases is to observe the affected patients at home over longer periods of time. Ballistocardiography [2] seems to be particularly suited for such patients since it allows to measure patients unobtrusively while they are in bed. Technically, a ballistocardiograph measures the vibrations of the body which are caused by the mechanical activity of the heart. Modern ballistocardiographs can be integrated into beds and are thus invisible to the patient.

Current algorithms to determine the heart rate from BCGs rely on spectral or time-domain methods that detect the periodicity of the signal by, for example, evaluating the auto-correlation function of the signal [3]–[5]. Since these approaches analyze signal segments which last for several seconds, only average heart rates over these periods are obtained. Beat-to-beat interval information, however, is necessary for advanced applications such as heart rate variability analysis or sleep staging. Some algorithms for beat-to-beat heart rate estimation from BCG signals have been proposed in the literature but they either require expensive sensor arrays [6] or sensors which have to be attached directly to the patient's body [7]. Other algorithms are designed to detect heart beats under normal physiological conditions [8]. However, arrhythmias are a widespread problem (approx. 2.2 million Americans are living with atrial fibrillations [9]). Hence, the assumption of a regularly beating heart does not hold for a significant fraction of the people to be monitored.

We present a novel algorithm for the estimation of beat-to-beat interval lengths from BCGs which works on signals recorded by a single sensor and which drops the assumptions of a regularly beating heart. The proposed algorithm uses unsupervised learning techniques to adapt to the high inter- and intra-subject variability of BCG recordings. Based on the learned features, three independent criteria are combined to obtain individual heart beat locations. These estimations are further refined to obtain accurate beat-to-beat interval length information. Based on the beat-to-beat interval lengths, a heart rate can be computed for each interval.

The following section details the signal acquisition system used to obtain the data for our study. Section III provides background information on BCGs while the proposed algorithm is presented in Section IV. We evaluate our method in Section V. The paper concludes with Section VI.

II. SIGNAL ACQUISITION

In this study, the ballistocardiograph consisted of a single sensing unit which was attached to one of the slats in a slatted bed frame. The sensing unit was composed of four strain gauges which formed a full Wheatstone bridge and which were glued to the center of the slat to measure its deformation. In order to optimally detect the heart activity, the instrumented slat was installed in the bed frame such that it resided approximately under the thorax region of the subject. An ordinary mattress was placed on top of the bed frame. Data were acquired at 128 Hz and were, after analogue amplification and denoising, digitized by means of a 12 bit ADC. Simultaneously, a lead I ECG was recorded for reference purposes.

III. PROPERTIES OF THE BALLISTOCARDIOGRAM

Signals recorded by ballistocardiographic systems consist of a superimposition of at least two different types of body movements: heart activity and respiratory motion. As breathing rate is usually lower than heart rate, the two signal components can be separated by standard time-domain filtering techniques [3]. Other body movements cause artifacts which might hamper or prevent the analysis of the signal for their duration.

BCG recordings are highly variable, much more so than ECGs. The waveform of a single heart beat changes depending on the subject and on how the subject is positioned on

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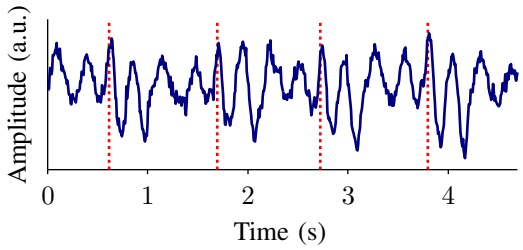

Fig. 1. BCG signal in which the respiratory motion was removed by high-pass filtering. The vertical dotted lines indicate the occurrence of R peaks in a simultaneously recorded ECG. Each heart beat leads to a self-repeating pattern consisting of several peaks in the BCG signal.

the bed with respect to the sensor. As shown in Fig. 1, each heart beat coincides with a repeating signal pattern consisting of multiple peaks instead of a single outstanding (and hence easily detectable) peak such as the R peak in ECGs. The increased number of peaks in the observed patterns might be caused by the propagation of the cardiac forces through the body as well as by potential resonances from under-damped parts of the measurement system.

IV. THE BEAT ALGORITHM

In the following, we present the Beat-to-beat Estimation by Adaptive Training (BEAT) algorithm which autonomously learns and detects BCG peak patterns corresponding to individual heart beats.

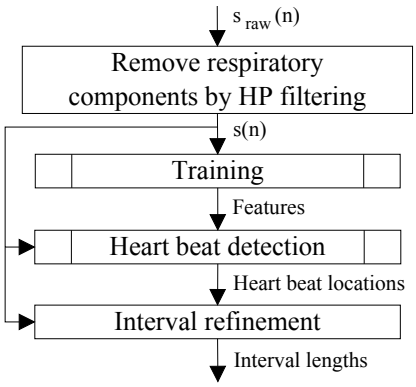

Fig. 2. Overview of the proposed algorithm.

A. Overview

A high-level overview of the BEAT algorithm is given by the data flowchart shown in Fig. 2. The incoming BCG signal, $s_{\text{raw}}(n)$, is filtered by a high-pass to remove the low-frequency respiratory components. A short segment of the filtered signal, $s(n)$, is then analyzed to determine the features of the heart beat in the so-called training phase. In the second phase, i.e. the heart beat detection phase, the remaining signal is scanned for heart beats based on the features that were learned during the training phase. This results in a list of estimated heart beat locations. In the final step, the estimated heart beat locations are used to produce a refined list of beat-to-beat interval lengths. Whenever subjects enter the bed or change their posture with respect to the BCG sensor, the training phase is repeated so that the algorithm can adapt to the changed heart beat pattern.

B. Training Phase

The training phase analyzes a short, e.g. 30 seconds long, BCG segment. First, a smoothed signal, $s_{\text{sm}}(n)$, is obtained by low-pass filtering $s(n)$. Peaks in this smoothed BCG signal are parameterized as shown in Fig. 3 in order to obtain a low-dimensional, rough description of the signal.

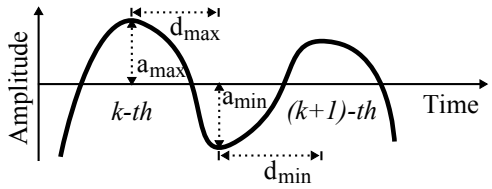

Fig. 3. Schematic showing the parameters used to describe a local maximum in the low-pass filtered BCG signal. The k-th peak is parameterized in terms of its amplitude a_{max}, the amplitude of the local minimum a_{min} between the k-th and the $(k+1)$-th peak, the distance d_{max} to this local minimum as well as the distance d_{min} from the local minimum to the local maximum of the $(k+1)$-th peak.

Each peak in $s_{\text{sm}}(n)$ is assigned a feature vector $\boldsymbol{f}_i$ containing the parameters of the peak itself and of the $N-1$ consecutive peaks (usually $N \in [4, 8]$):

$$\boldsymbol{f}_i = (a_{\text{max},i},\ d_{\text{max},i},\ a_{\text{min},i},\ d_{\text{min},i},\ \ldots,\ a_{\text{max},i+N-1},\ d_{\text{max},i+N-1},\ a_{\text{max},i+N-1},\ d_{\text{max},i+N-1})^{\text{T}}. \quad (1)$$

As such, the $4N$-dimensional feature vector $\boldsymbol{f}_i$ encodes the morphology of a segment of $s_{\text{sm}}(n)$ beginning at the i-th peak and encompassing a total of N peaks. The similarity between two feature vectors can be quantified, for instance, by the Euclidean distance between them.

Feature vectors which represent similar peak patterns are located close to each other in the feature space. Hence, we can discover reoccurring peak patterns by identifying clusters of similar feature vectors. For this purpose, we developed a modified version of the k-means clustering algorithm [10]. Fig. 4 and 5 examplarily show how the locations of the feature vectors are related to the relative positions of the first peak described by the respective vector. In this example, the heart beat pattern consists of four peaks (this is not always the case). We observe that four clusters of feature vectors are formed in the feature space and that the elements within each cluster correspond to segments of $s_{\text{sm}}(n)$ which begin at one particular peak of the repeating pattern.

Hence, each cluster represents a shifted version of the repeating pattern found in the BCG signal. Two parameters describing the morphology of the represented pattern are extracted from each cluster: the cluster center $\boldsymbol{c}_k$ which is the mean of all feature vectors belonging to the k-th cluster and the cluster prototype $p_k(n)$ which is the subsegment of $s_{\text{sm}}(n)$ from which the feature vector with minimum distance to $\boldsymbol{c}_k$ was derived.

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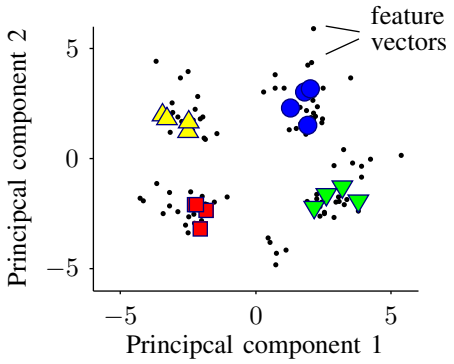

Fig. 4. Feature vectors from a training segment projected onto their first two principal components. The feature vectors form four clusters in the feature space. The highlighted vectors describe (overlapping) subsegments of Fig. 5 according to (1). The first peak of each subsegment in Fig. 5 is marked by the same symbol as the corresponding feature vector.

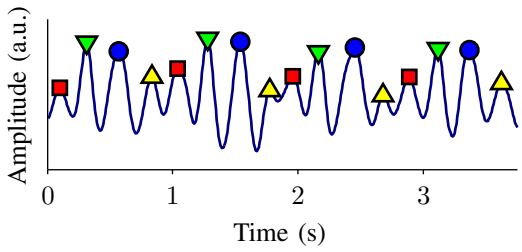

Fig. 5. A short segment of a smoothed BCG signal. Each peak is marked by the same symbol as the feature vector in Fig. 4 which corresponds to the subsegment beginning at this peak.

We complement the cluster analysis by also considering a modified version of the heart valve signal which was presented in [8]. The heart valve signal is believed to be related to the closure of the heart valves during the cardiac cycle. Instead of using a fixed bandpass to extract the heart valve signal, 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.

In conjunction with the modified heart valve signal, the parameter set $(\boldsymbol{c}_{\text{best}},\ p_{\text{best}}(n))$ which relates best to the heart beat is identified. For this purpose, each parameter set is used separately to detect heart beats in the training segment (see Subsection IV-C). Based on the results of these test runs, the most suitable set of parameters is determined by a set of heuristics.

C. Detection Phase

In order to detect heart beats in the BCG signal which lie outside the training segment, the algorithm uses the parameters extracted during the training phase. Based on these, three indicators are computed to identify heart beats in the remaining BCG signal:

1) minima in the Euclidean distance between the feature vectors of the remaining signal, which are obtained according to (1), and the cluster center $\boldsymbol{c}_{\text{best}}$ (indicating locations of subsegments which have similar morphology to the heart beat pattern encoded in the selected cluster);
2) maxima in the envelope of the cross-correlation between the cluster prototype $p_{\text{best}}(n)$ and the smoothed BCG signal (indicating a similar time-domain shape to the heart beat pattern);
3) maxima in the heart valve signal (indicating heart valve activity).

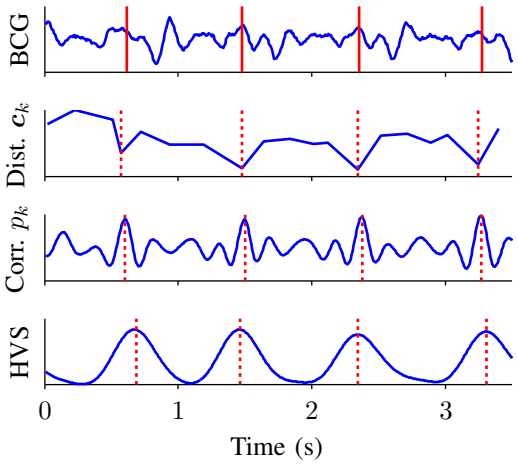

Fig. 6. BCG segment with the corresponding plots of the distance to the cluster center (Dist. c_k), the correlation between the BCG and the pattern prototype (Corr. p_k), and the heart valve signal (HVS). The vertical dotted lines indicate the location of the minima or maxima, respectively. By combining these indicators, heart beat locations in the BCG are estimated (indicated by solid vertical lines).

Figure 6 shows an example of the three indicator functions. Each extremum in these functions independently suggests a certain heart beat location. For each of these suggestions, a reliability score based on the shape of the minimum or maximum, respectively, is assigned. Prominent extrema are scored higher than extrema which are less distinct. The indicators are weighted by their reliability scores and then merged to obtain robust estimates of the location of heart beats in the BCG. Beat-to-beat heart rates can be derived from these time points by computing the time interval between two consecutive heart beats.

D. Interval Refinement

The heart beat locations obtained from the detection phase already provide robust estimates of the actual heart beat locations. However, we apply the refinement step proposed in [8] to further improve the resulting beat-to-beat interval estimates. Given two estimated heart beat locations, the BCG signal recorded during this interval should represent a characteristic pattern of a single heart beat. We refine each interval individually by determining when the corresponding characteristic pattern first repeats itself.

V. RESULTS

The performance of the BEAT algorithm was evaluated by comparing the estimated heart beat locations and beat-to-beat

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TABLE I
BEAT EVALUATION RESULTS

Total Signal Duration	h	12.5
Total Number of R peaks	#	47456
Coverage	%	96.87
False Negatives	%	0.28
False Positives	%	0.13
Average Interval Error	ms	14.16
Average Heart Rate Error	bpm	0.39

interval lengths to a simultaneously recorded ECG. In the recorded ECGs, the locations of the R peaks were detected by a modified Pan-Tompkins algorithm [11]. Furthermore, the resulting R-R intervals were computed.

The closest BCG heart beat location within a window of $\pm 0.25\,\mathrm{s}$ around each R peak was assigned to the R peak. Unassigned BCG heart beats were counted as *false positives* while R peaks to which no BCG heart beat was assigned were counted as *false negatives*. For each estimated interval, the absolute difference between its length and the length of the closest R-R interval was computed (*interval error*). According to [12], cardiac monitors are supposed to update their displayed heart rates every 10 seconds. Hence, we also computed the average error between the mean heart rates derived from the BCG over 10 seconds long intervals and those derived from the ECG over the same periods of time (*average heart rate error*). The percentage of the BCG signal that was automatically classified as artifact-free (*coverage*) was also recorded. Only the signal segments that are artifact-free were considered for the evaluation as the presence of artifacts impedes a reliable heart rate estimation.

We evaluated the proposed BEAT algorithm according to the above criteria. For the evaluation, 12.5 hours of BCG recordings containing 47456 heart beats were analyzed. The BCG signals were captured from adults (9 male, 8 female, ages 20–50) with no known heart conditions. Table I shows the algorithm's performance on this data set.

The algorithm achieved an average interval error of 14.16 ms. This value can be put into perspective by considering that the time interval between two consecutive sampling points in the BCG signal, which is sampled at 128 Hz, is 7.8 ms. This means that the average interval length was off by roughly two samples. The mean error of the heart rates averaged over 10 seconds was 0.39 bpm. Considering the integer displays on cardiac monitors, the displayed ECG and BCG heart rates would have been identical on average.

Figure 7 compares 15 consecutive beat-to-beat heart rates that were derived from the BCG with those that were derived from the ECG. In this particular case, consecutive beat-to-beat heart rates differed by up to 20 bpm. We see that the BEAT algorithm can follow significant irregular variations of the beat-to-beat heart rates.

VI. CONCLUSION

We presented a novel algorithm for the estimation of beat-to-beat heart rates from highly variable BCG signals.

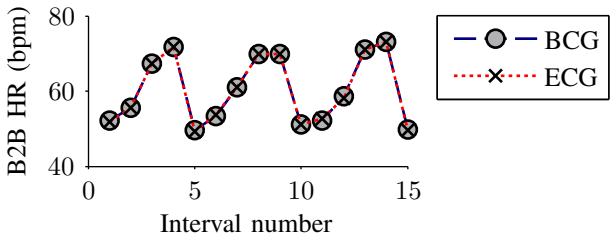

Fig. 7. Comparison of beat-to-beat heart rates derived from 15 consecutive beat-to-beat intervals of the BCG with those derived from the ECG.

A modified k-means clustering algorithm was applied to a parameterized version of the BCG signal to extract the shapes of repeating patterns in the signal. Using the parameters derived during a training phase, heart beats were located in the remaining BCG signal by merging the results of three independent indicator functions. Through this method, we were able to achieve robust heart rate estimation on BCG data with beat-to-beat accuracy. The presented algorithm can process BCGs on-line as well as off-line.

In future work, we want to improve the robustness of the training phase, automatically detect gradual changes to the signal which would require a re-training, as well as evaluate the algorithm's ability to detect arrhythmias in BCGs.

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