Contact-Free Piezo Electric Sensor used for Real-Time Analysis of Inter Beat Interval Series

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Abstract

In heart rate monitoring, the Electrocardiogram (ECG) is commonly used and is considered to be the gold standard in the field. However, long term monitoring with ECG is rarely used except for ICU and 24-hours Holter. Prolonged cardiac monitoring in various setups can be achieved using a Ballistocardiogram (BCG), which serves as a convenient way for contact free monitoring of the heart activity.

This study was aimed to assess the potential of measuring cardiac Inter Beat Interval (IBI) series in real-time using a BCG signal using a contact-free piezo-electric sensor placed under the mattress (EarlySense Ltd.). In this paper, we evaluated three real-time novel algorithm that provide IBI measurement, predicated IBI measurement accuracy and IBI statistic.

The performance of these algorithms was evaluated using IBI series derived from one-lead ECG signal. The results support the claim that under the mattress piezo-electric sensor can be used to accurately measure IBI in real-time, and establish the basis for Heart Rate Variability (HRV) analysis.

1. Introduction

Ballistocardiography depicts the acceleration or recoil of the body that is concomitant to each ejection of blood from the ventricle to the aorta [1]. It has drawn special attention in the past couple of years since it enables long-term measurement of heart rate activity without wearing any sensors or electrodes on the body. A BCG signal can be obtained using sensors placed on a chair, on a bed, on a weighing scale or directly on the subject [2].

Measurement of the average heart rate using under the mattress piezo electric sensor (EarlySense Ltd.) is commercially available since 2009 and was already widely validated [3] and tested [4]. In this work we intended to assess the ability of such sensors to measure each IBI as the basis for an accurate beat-by-beat analysis of the heart activity. This can help to detect several types of cardiac abnormalities and can also help provide a precise spectral analysis of the variation in the IBI series, used for heart rate variability analysis, sympathovagal balance (stress) measurement and sleep staging.

In a BCG signal, the beats are less pronounced in comparison to an ECG signal, thus, the task of detecting each heartbeat from a BCG signal is considerably more difficult. This occurs due to two main reasons. First, the signal to noise ratio (SNR) of the BCG signal is much lower than the SNR of the ECG signal. Second, the variability in the composition and thickness of the mattress, the user position with respect to the sensor, the body motion and the changes in respiration amplitude can all have tremendous effect on the BCG signal, and thus make the detection of the heart beats to be more difficult.

In this work, the performance of three novel algorithms was tested. The first is used for real-time IBI measurement obtained only while the user is lying in bed. The second is used for real-time classification of the beats measured using the first algorithm based on anticipated accuracy. The third is used to acquire discrete IBI distribution maps throughout the night recording, based on IBI data from overlapping 15 minutes windows. The Algorithms were designed with low algorithmic complexity to allow a real-time analysis which can be applied in cellular phones.

2. Methods

2.1. Signal acquisition and reference

The BCG data were acquired from 25 home sleep recordings of 14 healthy individuals in a two-in-bed setting. The signal was acquired using a piezo-electric sensor placed beneath the mattress under the tested subject [3]. The heart rate of each subject was measured using a medical grade and FDA approved ECG device (Embletta, ResMed, USA) which recorded the heart rate using a one-lead ECG. These over-night recordings produced a test set which consists of nearly 500,000 IBIs, hence forth termed “data set 1”. Additional data, hence forth termed “data set 2”, was acquired from several recordings of individuals with different prominent heart arrhythmia. The recordings were done in a one-in-bed setting. Their cardiac activity was monitored in real-time using an ECG monitor.

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2.2. Measurement algorithm

This algorithm produces a continuous IBI measurements, which consists of measurements acquired only while the subject is lying in bed. The algorithm can be broken down into six steps:

1. The raw BCG signal is processed using a bank of finite impulse response (FIR) bandpass filter with different passing frequencies and with an Empirical Mode Decomposition (EMD) filter [3].

Steps 2-5 are applied separately to each filtered signals.

2. Peak detection is performed based on the filtered signal morphology.
3. An approximate IBI is computed using average heart rate estimation based on spectral features of the raw signal and IBI statistics obtained from previous IBIs measured. The IBI approximation dictates a localized search area to find the signal peaks induced by the cardiac activity.
4. Several peaks, suspected as induced by the cardiac activity, are chosen in each localized search area based on the filtered signal morphological features.
5. The IBI measurement is computed based on selecting only one peak in every localized search area. The selection of which peaks most accurately characterize the IBI is based on morphological similarity and distance similarity between the peaks of three consecutive localized search areas.

Step 6 is applied on all filtered signals together.

6. For each IBI, the measurements obtained using each of the filters according to step 5 are evaluated according to anticipated accuracy. The most accurate measurement serves as the selected IBI measurement. The accuracy criterion depends on morphological characteristics of the filtered signal, local IBI duration statistics and average heart rate estimation based on spectral features.

2.3. Classification algorithm

Binomial logistic regression model was used to classify each IBI measured using the first algorithm into one out of three groups according to anticipated measurement accuracy. The regression parameters were based on morphological attributes of the BCG signal, average heart rate estimated from spectral analysis of the BCG signal and IBI statistics of adjacent beats.

The regression coefficients were determined using a numerical optimization method called particle swarm optimization (PSO, [5]). Data set 1 was selected as the test set for optimizing the regression coefficients. The optimization was tuned to select a subset containing 70% of the all IBIs acquired using the measurement algorithm with the maximum number of IBI measurements with absolute measurement error of 17 milliseconds or less compared to the ECG derived IBI.

2.4. IBI distribution estimation algorithm

The dependence of the first algorithm on IBI history may lead to tracing difficulties when the IBI data is very variable or contains abrupt changes. As such, an additional algorithm was designed which largely depends on signal morphology and only slightly depends on IBI history. This algorithm was designed with the aim of achieving IBI statistics, particularly for patients with variable IBI, such as, patients with prominent Respiratory Sinus Arrhythmia (RSA), and patients with heart rhythm abnormalities.

This algorithm produces a discrete IBI distribution map, where each one dimensional distribution is based on the IBIs measured in a 15 minute time windows. The temporal overlap between adjacent time windows was chosen to be 13 minutes and the IBI's discrete sampling resolution was selected to be 50 milliseconds. The beat detection stage was designed to work in real-time and measure only part of the continuous IBI set with only slight consideration to IBI history. The algorithm can be summarized as follows:

1. Filtering the raw BCG signal using a set of FIR filters, each with a unique frequency response, used to capture the cardiac signal.

Steps 2, 3 and 4 are performed on each one of the filtered signals individually.

2. Performing a peak detection based on morphological characteristics of the filtered signal.
3. Selection of valid peaks which can be used for IBI measurement. The selection is based on morphological features of the filtered signal, morphological similarity between adjacent peaks and real-time measurements of averaged heart rate.

Steps 4 and 5 are applied only at the end of the time frame of each one dimensional distribution.

4. Applying an outlier exclusion scheme which rests on concepts taken from the local outlier filter (LOF) algorithm [4]. The algorithm examines all the detected IBIs in the 15-minute window and determines which can be used to estimate the discrete distribution and which should not be used. The decision is based on average distance from neighbours in a one-dimensional parameter space, where the parameter examined is the IBI.

Step 5 is applied on data acquired from all the filtered signals together.

5. Selecting the largest IBIs set as representing the discrete distribution at the examined time frame. If the size of all sets is smaller than a predefined size, no distribution is calculated for the time frame.

2.5. Performance evaluation

Lead II ECG was sampled at 200Hz and recorded using

a portable device. This was used to extract the reference continuous IBI sets Areas in the signal in which ECG data was distorted were excluded from the analysis. The reference data was used to assess the accuracy on a beat by beat level of the continuous IBI set obtained using the measurement algorithm and the IBI subset classified as most accurate according to the classification algorithm.

The ECG data for all the two-in-bed patients was used also to generate a discrete IBI distribution maps with the same features (time overlap and discrete sampling resolution) as the IBI distribution maps computed using the third algorithm. Theses maps were used to assess the performance of the third algorithm. The similarity between the maps was evaluated per distribution map using a distance score based on chi-square distance:

$$Distance\ Score = \frac{1}{M}\sum_{k=1}^{M}\sum_{i=1}^{N}\frac{\left(p_{i,k}-q_{i,k}\right)^2}{p_{i,k}+q_{i,k}}$$

Where M represents the number of time windows examined, N is the number of observations of the discrete IBI distribution, i represent the i-th discrete sample and k represents the k-th time frame, $p_{i,k}$ represents the estimated discrete IBI distribution map, $q_{i,k}$ represents the reference discrete IBI distribution map.

The distance score was only calculated for time frames in which the algorithm produced a valid discrete distribution (according to step 5). This distance score ranges between 0 and 2, where 0 represents an exact match between the distribution maps and 2 represents a two completely different discrete distribution maps.

Data set 2 was also used to assess the quality of the IBI distribution algorithm. The data was compared both visually and according to the similarity criteria to gain insights whether this algorithm can also be used to analyze IBI statistics of patients with arrhythmia.

3. Results

3.1. Measurement algorithm

The real-time IBI measurements were compared on a beat-by-beat level to the IBIs from data set 1. Table 1 summarizes the percent of IBIs from the entire IBI set which were accurately measured under different measurement error thresholds.

Table 1. Real-time IBI measurement accuracy results.

Maximum Absolute Measurement Error [millisecond]	Percent of IBI correctly measured from the entire IBI set
4.15	42.17
8.30	58.79
12.45	68.23
20.75	77.44

Due to sampling frequency limitations, the results are displayed in table 1 with a discrete resolution of ~4.15 millisecond, corresponding to a sampling resolution of ~ 240 Hertz. As can be seen in table 1, nearly 60% of the IBIs were measured with an absolute error of up to 8.3 milliseconds and almost 78% of the IBIs with an absolute error of up to 20.75 milliseconds.

3.2. Classification algorithm

The performance evaluation has shown that the logistic regression classification method was able to detect a subset of IBI measurement which are, on average, more accurately measured than the entire set. The measurement accuracy of the subset classified as more accurate showed a significant improvement comparing to the entire IBI set. In this subset, 90% of the IBIs had an absolute measurement error of 20.75 milliseconds or less, which indicates an increase of almost 13% compared to the entire set, and 70% of the IBIs, had an absolute measurement error of 8.3 milliseconds or less, which indicates an increase of nearly 12%. This subset average absolute measurement error equals to 13.2 milliseconds.

3.3. IBI distribution estimation algorithm

The performance evaluation has shown significant similarity between the estimated discrete distribution maps and reference discrete distribution maps. The evaluation yielded an average distance score of 0.128 with a detection rate of nearly 100%, where 80% of the night recordings obtained a distance score of 0.15 or lower.

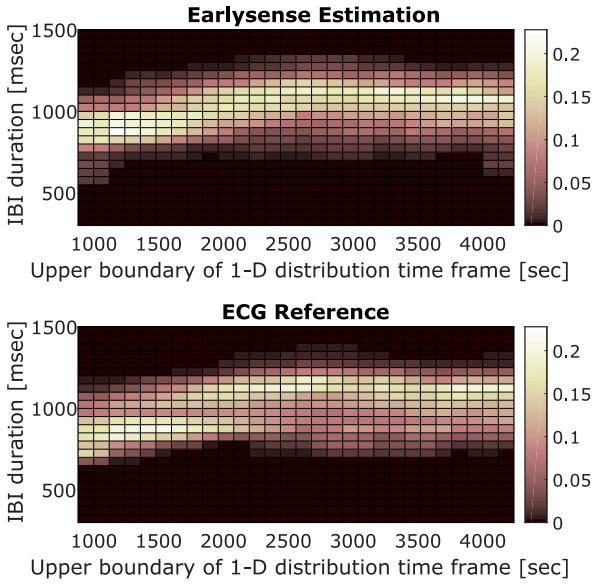

Figure 1. Reference and estimated IBI distributions map of a subject with prominent respiratory sinus arrhythmia.

Testing this algorithm on several patients with variable heart rhythms, i.e., data set 2, has also shown very promising results. As can be seen in figure 1, the algorithm was able to accurately estimate the discrete IBI distribution of a young girl with prominent respiratory sinus arrhythmia (RSA). The algorithm demonstrates a potential to accurately trace changes in the IBI distribution throughout this BCG recording.

The algorithm was also tested on another subject, suffering from atrial fibrillation. As can be seen in figure 2, the algorithm was successful in detecting heart beat rhythm irregularity, which causes continuous alternation between a longer heart beat (around 800 milliseconds) and a shorter heart beat (around 450 milliseconds). From the algorithm results, we can also determine with some accuracy the ratio between the number of longer beat and the number of shorter beats (according to the reference – 3:1, according to the estimation – 5:1).

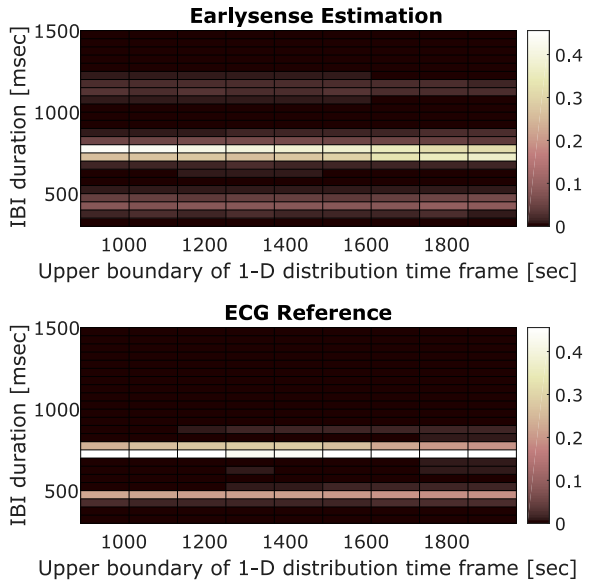

Figure 2. Reference and estimated IBI distributions map of a subject suffering from atrial fibrillation (AFib).

4. Discussion and conclusions

The purpose of this study was to evaluate the potential of obtaining accurate IBI measurements and statistics from a BCG signal acquired using a contact free piezoelectric sensor placed under the mattress. This study displayed three novel real-time algorithms used for measuring the IBI, classifying them according to suspected accuracy and estimating the IBI distribution in a 15 minute windows.

The results provide compelling evidence that the first algorithm presented can accurately measure the cardiac IBI in real-time with relatively low algorithmic complexity. The second algorithm was shown to provide a reliable assessment of accuracy of the real-time IBI measurement obtained using the first algorithm. The evaluation has also shown that the third algorithm can potentially serve as a future indicator of specific arrhythmia, when the arrhythmia occurs frequently and consistently.

This proven ability to measure accurate IBI on a beat-by-beat basis enables Heart Rate Variability (analysis) with this contact free sensor. It is used as the basis for calculations of the sympathovagal balance which is used for stress evaluations, as well as for sleep staging.

For a healthy heart during homeostasis condition, each electrical triggering of the ventricle, reflected by the QRS and ECG, is followed by an actual contraction of the ventricle, reflected by the BCG. Measuring HR, either way, results in a similar IBI series. However when the R-J interval undergoes physiological-induced changes, it can generate slight differences between compared IBIs [6]. This upper limit to the similarity between IBI derived by a BCG signal and IBI derived by an ECG signal, and it can partly explain the differences shown in the results section.

We believe that the suggested algorithms can be further improved in the future to provide more accurate IBI results and statistics harming the real-time capabilities of the suggested algorithms.

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