LOW-POWER CONTINUOUS HEART AND RESPIRATION RATES MONITORING ON WEARABLE DEVICES

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ABSTRACT

A low-power consumption approach for continuous heart rate (HR) and respiration rate (RR) monitoring for wearables is proposed. The approach provides a fusion of algorithms for HR/RR monitoring in calm and active states. For both states the algorithms process only accelerometer data. In calm state HR/RR tracking algorithm is based on a ballistocardiogram (BCG) processing. It shows 6.1 bpm root-mean-square error (RMSE) for HR monitoring and 1.9 breaths per minute RMSE for RR monitoring. In the active state HR and RR trends are calculated by machine-learning (ML) model adding a special post-processing procedure (RMSE = 7.5 bpm). The complete approach allows reducing power consumption up to 70%, compared with the state-of-the-art approach that uses a photoplethysmogram (PPG) sensor. The work results in the background for energy effective continuous monitoring of human physiological parameters by wearable devices.

***Index Terms*—** heart rate**,** respiration rate, wearable, accelerometer, ballistocardiogram, machine-learning model.

1. INTRODUCTION

In 2017 the healthcare wearables market accounted for US$6.8 billion of the current US$25 billion wearables market [1] and in the nearest future health oriented applications and services will dominate on this market [2].

HR and RR are the most important vital signs along with body temperature and blood pressures. In contrast to a single measurement, continuous monitoring of these vital signs allows to estimate a lot of lifestyle and health features [3-7]. Long-term monitoring of HR/RR provides new information about human wellbeing and is a unique feature of wearables.

Wide spread approach for HR estimation by wearables is using optical photoplethysmogram (PPG) sensors [8-10]. The drawback of using such sensors is high power consumption. It does not allow providing long-term continuous monitoring, especially for smartwatches which simultaneously provide other services or for wireless earplugs with limited battery capacity. So, the main goal of this work is to provide a long-term continuous HR/RR monitoring solution for wearable devices.

2. STRUCTURE OF PROPOSED MONITORING SYSTEM

The proposed approach for low-power continuous HR/RR monitoring system consists of a two-branch structure (see Fig. 1). As an input, we use data from the accelerometer and/or gyroscope sensors. The first branch is used for BCG based HR/RR monitoring in a calm state, and the second is for HR/RR estimation during activities. In order to switch branches we employ an activity detector that uses a threshold of accelerometer variance as a criterion of calm/activity classification. The branches are combined by a post-processing procedure.

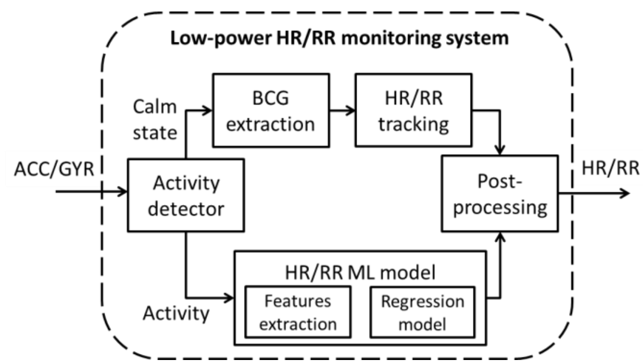


Fig. 1: A structure of low-power continuous HR/RR monitoring system.

The first branch provides HR/RR monitoring in a calm state in real-world positions (sitting, standing, lying) with low motions. The method is based on an informative signal component (HR/RR dominant frequency) tracked by a novel spectrum energy dissipation and accumulation method.

The second branch is used for HR/RR estimation during user’s activities (walking, running, treadmill). In this case, it is impossible to extract the BCG signal from accelerometer/gyroscope (ACC/GYR) and thus to directly measure HR/RR. At the same time, the intensity of motion, measured by accelerometer and/or gyroscope, allows estimating HR/RR trend by using a ML technique. By using this trend and the reference points from the first branch, the post-processing algorithm restores the actual HR/RR values.

The proposed low-power continuous monitoring system could be combined with the state-of-the-art solutions for HR or RR monitoring systems with the aim to optimize the accuracy/power consumption characteristic.

3. BCG BASED HR/RR MONITORING

It is possible to extract information about HR and RR from BCG signal measured on the user's wrist [11-14]. In this work, we implement a novel algorithm for BCG extraction from ACC and/or GYR data of wrist-worn devices.

The proposed algorithm of HR/RR monitoring is based on BCG data, and it contains three main stages of ACC/GYR data processing:

1) BCG envelope extraction for each dimension of ACC/GYR signals;
2) evaluation of cross-spectrum between each filtered BCG envelope components;
3) peak tracking algorithm.

The classical amplitude-modulation detector scheme [15] is used for the BCG envelope extraction. The cutoff frequencies of Butterwort band-pass and low-pass filters are 8 - 14 Hz and 5 Hz correspondingly for HR monitoring and 5 - 15 Hz and 1.7 Hz for RR monitoring. Sampling frequency of input signals (20 or 100 Hz) depends on type of smartwatch. After BCG envelope extraction, a downsampling procedure is performed. For HR estimation we use 10 Hz sampling frequency and for RR – 4 Hz sampling frequency.

The cross-spectrums between different orientation channels of the input signal (ACC or/and GYR) pick out common spectral components in the signals. HR/RR tracking is based on an assumption that corresponding to HR spectrum peak is stable and presented on several measuring channels (x, y, z). This approach also provides robustness to the user's postures. We use a simple weighted sum scheme for cross-spectrum merging:

$$\bar{S}_{\Sigma} = kx * kz * \bar{S}_{xz} + kx * ky * \bar{S}_{xy} + ky * kz * \bar{S}_{yz}, \quad (1)$$

where: $\bar{S}_{\Sigma}$ – result sum of cross-spectrums; kx, ky, kz – are weighted coefficients that characterize the quality of the corresponded ACC/GYR signal component.

Weighted coefficients are dynamically calculated based on the energy of each ACC/GYR signal component. If some non-stationary artifacts are detected in particular component then corresponded weighted coefficient tends to zero.

HR/RR monitoring is provided by the dominant peak tracking of the cross-spectrum sum. The tracking is based on a novel spectrum energy dissipation and accumulation method. The main goal of the proposed method is to provide a simple and effective mechanism for stationary components tracking in signal with high nonstationary noise.

The proposed approach is based on similar principles as the «seam carving» algorithm that is widely used in image compression [16]. Classical seam carving uses an energy function defining the importance of pixels, and a seam is a connected path of low energy pixels crossing the image.

In our case, we define «seam» as a connected path of high energy component in the spectrogram of a signal. There are two main steps in this method (see Fig. 2ab):

1) spectrum energy accumulation and dissipation;
2) local maxima tracking.

For dynamic spectrum energy accumulation and dissipation we implement the following recursive formula:

$$E_{t,j} = K * max\left(E_{t-1,j-N} : E_{t-1,j+N}\right) + S_{t,j}, \quad (2)$$

where: $E_{t,j}$ is the resulted accumulated spectrum energy on j-th frequency value and in t-th time moment; K is the forgetting factor coefficient; N = W/2-1; W is the size of dissipation window; $S_{t,j}$ is the input spectrum value on j-th frequency value and in t-th time moment.

As an input spectrum, we use the sum of cross-spectrums (Eq. 1). The forgetting factor coefficient (K) allows to control "memory" of accumulation. In the example presented in Fig. 2a (K = 1). In our experiment, we use a forgetting factor coefficient in the range of 0.7- 0.9.

Dissipation of spectrum energy is achieved by using the maximum function in certain tracking window around each frequency point in one spectrum. We use a dissipation window with W = 5 (see Fig. 2a). Dissipation allows making connections between the local spectrum maxima in different time moments. As a result, we get a spectrum energy dissipation diagram (see. Fig. 2c).

Tracking of a local maximum started from some initial point that is defined by the initial capture algorithm and is carried out according to a formula:

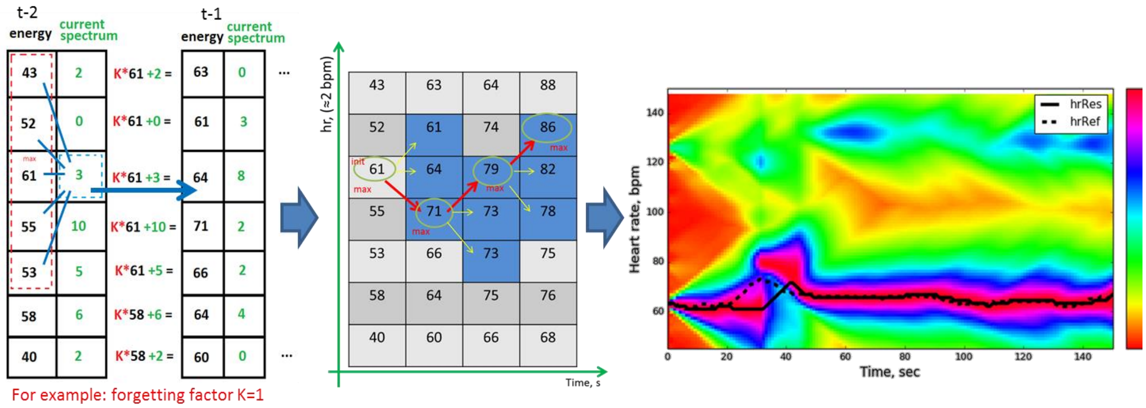
$$F_t = argmax\left(E_{t,j-M} : E_{t,j+M}\right), \quad (3)$$

where: F_t – the resulted frequency coordinate of local maximum in t-th time moment; M = L/2-1; L – size of the tracking window (L = 3).

As the drawback of the proposed method, we can admit the low dynamic of HR tracking. Thus, this method can be implemented in the cases when HR doesn't have rapid changes.

4. HEART RATE ESTIMATION DURING ACTIVITIES

HR monitoring during physical activities is a very popular and important feature of wearable devices. In most cases, it is realized by PPG-based methods. The drawbacks of this method are: sensitively to motions; the necessity of good contact between skin and sensor; high power consumption.



a) Spectrum energy accumulation and dissipation

b) Local spectrum maxima tracking

c) Result spectrum dissipation diagram with referent and estimated HR values

Fig. 2: Spectrum energy dissipation and accumulation tracking method

To prolong battery life and provide robustness for motion artifacts, we propose a scheme with accelerometer based on-line HR model and a special post-processing procedure (see. Fig. 1). On-line HR model estimates the trend of HR changes during activity. Post-processing procedure optimizes this trend location according to the referent HR points from HR estimation algorithm (it is implemented based on ACC/PPG or fusion sensors data).

HR values are highly correlated with the duration and intensity of activity [17]. For the most popular sports activities (walking, running, swimming, etc.) the intensity of the activity can be uniquely determined by accelerometer data. Based on this point we create the ML model for estimating the trend of HR values that uses four hand-crafted accelerometer features.

Based on the locally collected dataset, we have synthesized the ML model for HR trend estimation during user activity. The dataset contains 300 logs with walking and running activities collected by involving 40 respondents. Each log has duration from 5 to 60 minutes. Respondents have different physical levels and their age is from 20 to 50.

Results of the online HR model are used by the special post-processing algorithm to fit the known HR values and to fill the gaps in which unknown or unreliable HR values occur. The proposed post-processing algorithm is based on an optimization shift between HR trend and reliable HR values. We use a weighted sum of approximation error with respect to the reliability of HR estimation results as fitness function. Testing results are presented in paragraph 5.2.

5. APPROACH EVALUATION

The proposed HR monitoring algorithm was tested on a locally collected dataset of 42 respondents (25 - male, 17 - female) with the average age of 29 years (from 20 to 52 years). The dataset contains 250 hours of ACC/GYR/PPG signals, collected on Samsung Gear S2/S3/Fit2/Sport smartwatches and labeled with reference HR value from Polar H7 belt. The logs represent both calm and active states and real-life postures and activities: sleeping, sitting, standing, lying, walking, running, and treadmill training of the respondents.

5.1. Results of HR and RR estimation in calm states

BCG based algorithm of HR estimation was tested on logs with four types of calm or near calm condition: standing, sitting, lying and sleeping. The BCG extraction was tested on the following conditions:

- ACC databased;
- GYR databased;
- ACC+GYR data based.

The best accuracy was archived with complex ACC+GYR data usage, but this approach has high power consumption because of GYR sensor usage. ACC based approach is the most energy saving withal, and it provides a sufficient average accuracy of 6.1 RMSE bpm, see Fig. 3.

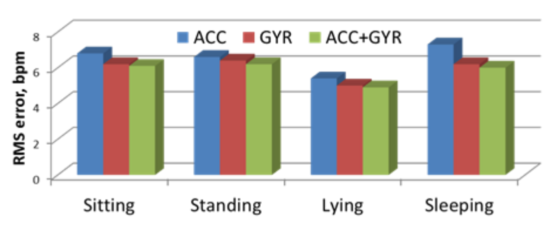


Fig. 3: Results of algorithm accuracy evaluation

The RR monitoring algorithm was tested on 98 logs of a night sleep collected by the sleep center in Korea. A thermistor respiratory monitor was used as a referent RR monitoring device. RMSE of RR monitoring is 1.9 breaths per minute.

5.2. Results of HR estimation during activities

The on-line HR model and post-processing procedure were tested based on logs with activities: running, walking, treadmill and hiking. These logs weren't included in the train set that was used in ML model synthesis procedure. Each test log has a duration of 3-10 minutes. For testing, we use reference HR values at 10 first and 10 last seconds in every log as reliable HR values. HR values in the remaining log points were estimated by the proposed post-processing algorithm. Test results are presented in Table 1. An example of the proposed HR monitoring approach during running activity is shown in Fig. 4.

Table 1: Evaluation results of HR estimation during activities

Activity	Test Log Quantity	RMS error, bpm
Running	28	9.9
Walking	36	7.4
Treadmill	152	7.15
Hiking	66	7.1

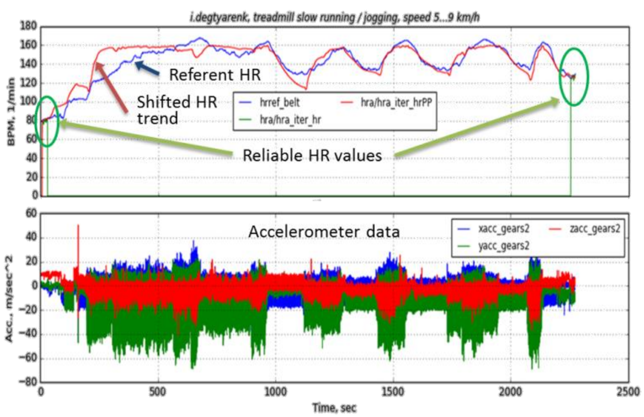


Fig. 4: Results of accelerometer-based HR monitoring during running activity

5.3. Accuracy and power consumption estimation in different modes algorithm

Experiments for power consumption estimation of different algorithm modes were executed on Samsung Gear Sport smartwatches with 300 mAh battery. Average battery per hour usage time was obtained by logging the battery discharge from 100% to 5% range for the corresponding combination of sensors and same settings of other peripheral (BT-off, WiFi-off, notifications – off, display level - 1 etc.). Sampling rates are: 20Hz for PPG signal and 100Hz for the accelerometer. Measurements were made for the PPG-sensor state from permanently switched-on (state-of-the-art) via periodically switched on PPG to permanently switched-off (low-power approach), see Fig. 5.

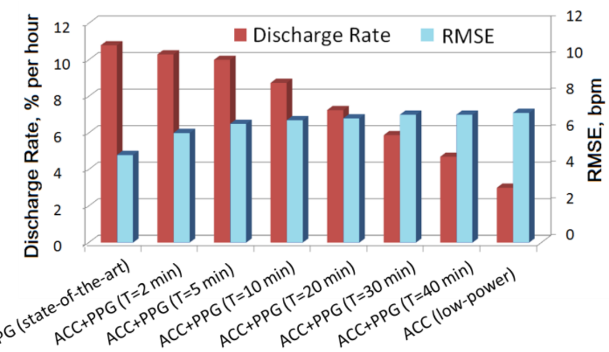


Fig. 5: Tradeoff between accuracy and discharge rate. Period of PPG sensor usage (T) is presented in the brackets.

The dependencies in Fig. 5 show a trade-off between accuracy and power consumption. The optimal mode depends on real-world implementation target. Proposed low-power approach allows to decline power consumption by 70% (from 10.8 to 3.2 percent per hour) compared to the state-of-the-art approach. Simultaneously, the accuracy falls by 2.2 bpm (from 4.3 to 6.5).

6. CONCLUSION

Long-term HR/RR monitoring is achieved by the fusion of separate monitoring algorithms for calm and active states. In the calm state, HR/RR is monitored by direct calculation. In the active state, HR/RR trend is calculated via machine learning. The continuous monitoring is achieved by combining the trend during activity and actual values in the calm state by the post-processing algorithm.

Usage of the novel structure of BCG signal extraction based on cross-spectrums of ACC channels and energy dissipation algorithm provides HR and RR continuous monitoring with HR RMSE of 6.1 bpm and RR RMSE of 1.9 breaths per minutes. The approach provides background for 24-hours HR/RR monitoring, i.e. during sleep.

The machine learning model for HR trend estimation during activities only by using ACC features was implemented for the first time. The conjunction of the HR trend with actual HR values (estimated in a calm state before and after activity) estimates HR values during activity. This approach provides accuracy of 7.5 bpm sufficient for most use cases of HR monitor usage (HR zone detection during fitness, HR trend monitoring, etc.).

The proposed solutions extend the duration of continuous HR monitoring up to 70% compared to the state-of-the-art approach based on the PPG signal.

Combination of the above methods provides the long-term term continuous HR/RR monitoring for wearables devices. It is applicable for existing and future wearables equipped with accelerometer sensor.

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