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HEART RATE ESTIMATION THROUGH AUTOCORRELATION FROM SINGLE AXIS ACCELEROMETER OF SMARTPHONE

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***Abstract*— Mobile phone has become a basic necessity in our daily life. With more than 7 billion mobile phone users worldwide, the prevalence of smartphones has led to an increase in applications for health monitoring. This paper suggests an autocorrelation-based technique for predicting Heart Rate (HR) from single-axis accelerometer data, utilizing the integrated motion sensor for acceleration in mobile phones. To extract the cardiac signal, the proposed method employs a combination of Butterworth and Bessel filters to preprocess the accelerometer data and isolate periodic segments corresponding to heartbeats. A dataset of simultaneous accelerometer and ECG from 300 individuals with Atrial Fibrillation (AF) and Sinus Rhythum (SR) were used to evaluate the technique. The HR is measured by comparing the difference between the first two peaks in valid segments of each subject. For subjects in SR, the method demonstrated high accuracy with a Mean Absolute Error (MAE) of 4.54 Beats per Minute (BPM), aligning with clinical accuracy standards. However, a higher MAE of 15.7 BPM was observed in AF subjects, highlighting the need for further refinement in arrhythmic populations. Future research will focus on enhancing accuracy across diverse cardiac conditions and expanding validation across larger and more diverse datasets.**

I. INTRODUCTION

In 2014, approximately 1 billion individuals used mobile phones. This number has surged to over 7 billion and is projected to reach 7.6 billion by 2025 [1]. While smartphones equipped with accelerometers and gyroscopes are widely used for general activity tracking, these sensors are also integral components of high-precision, medically certified devices. In the medical field, accelerometers and gyroscopes are used in specialized devices for health monitoring, providing critical data on physical activity, movement patterns, and vital health parameters. The advanced motion-sensing capabilities of mobile phones enable accurate and reliable monitoring of cardiac conditions and other health metrics, meeting stringent standards required for medical applications. These devices represent a significant leap in healthcare technology, delivering precise, clinically validated insights for diagnostics and continuous health monitoring [2].

Recent developments have investigated the use of accelerometer data for HR estimation using techniques such as gyrocardiography (GCG) and seismocardiography (SCG) [3][4]. Highlighting its potential in non-invasive cardiac monitoring, Lahdenoja et al. presented a combined SCG and GCG technique for HR and heart rate variability (HRV) assessment [5]. Additionally, Laurino et al. used accelerometers incorporated into mattresses to develop a moving auto-correlation window technique that extracted HR from ballistocardiography (BCG) signals. The technique performed satisfactorily when compared to references from electrocardiograms (ECGs) [6]. Similarly, Landreani et al. obtained heart rate using smartphone accelerometers through wavelet denoising technique and obtained an accuracy of more than 95 percent [7]. Heart rate from SCG was also estimated by Jafari Tadi et al by using Hilbert transformation [8]. The viability of using accelerometer-derived data for precise and discrete HR monitoring is demonstrated by these investigations.

This work presents a unique approach for estimating HR from single-axis accelerometer data using an autocorrelation method. To identify periodic components that correspond to heartbeats, our method first preprocesses the accelerometer signals using a variety of filtering approaches, and then autocorrelation analysis was applied to the signals. We verify our approach on a dataset of simultaneous ECG and accelerometer recordings, showing that our algorithm produces reliable HR estimation on par with ECG references. This study highlights the potential of continuous and non-intrusive cardiac monitoring utilizing single-axis accelerometer data.

II. METHODS AND MATERIALS

Figure 1 shows the overview of the entire signal processing pipeline applied in this work to compare the HR measured by an accelerometer to the pulse obtained from the ECG. The entire signal processing applied in this work was performed on Python (version 3.12.4) with open source Scipy libraries. The processing time for these 300 signals was less than 3 minutes(min) on 13th Gen Intel(R) Core (TM) i7-1355U 1.70 GHz.

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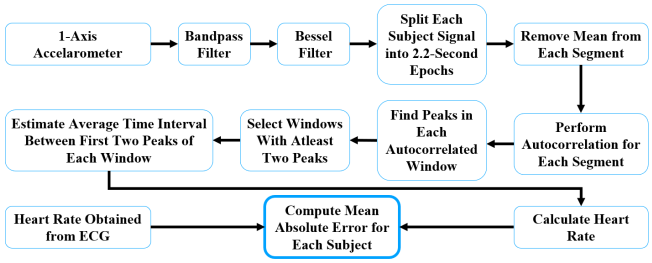
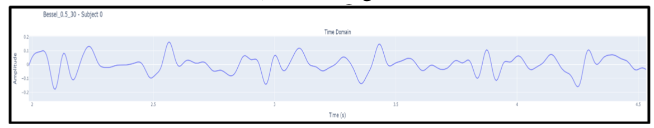


Fig. 1: Overview of the overall Signal Processing Pipeline

(a) Raw Signal



(b) Filtered Signal

Fig. 2: Overview of the overall Signal Processing Pipeline

A. DataSet

Jaakkola et al. previously used and reported the dataset used in this current research. Ethical approval for the data collection was obtained from the institutional review board. There were 300 participants, 150 of whom have SR and 150 of whom have AF. Between April and September 2017, these volunteers were gathered from Turku University Hospital's internal medicine and cardiology wards in Finland. After acquiring prior consent, a Sony Xperia smartphone was put on the sternum to capture a 3-min GCG and SCG of each participant. All subjects were lying down during the data collection to ensure consistency in posture. The Philips IntelliVue MX40 system, the gold standard for rhythm evaluation, was used to simultaneously capture a 5-lead telemetry ECG recording. The HR was obtained from the ECG recordings for each subject. The participants' ages ranged from 18 to 97 years old, with a mean age of 62. There were 178 men and 122 women in the cohort, guaranteeing equal representation of each sex.The mean Body Mass Index (BMI) for SR subjects was 27.4 kg m ^{2}, where as the mean BMI for AF subjects was 28.9 kg m ^{2} in our study [9].

B. Signal Processing

A set of 7 filters were initially selected for this research work. These filters included Butterworth, Two-stage Butterworth, Chebyshev filter, Elliptic filter, Bessel filter, Savitzky-Golay filter and Kalman filter [4],[10],[11]. The filters were applied in sequential order till depth of 4. While initial filter layers significantly reduced error, further increase in depth beyond three filters yielded only marginal improvements. It is noteworthy that the selection of these filters and their respective parameters was based on extensive experimentation, with the final configuration chosen according to the criterion of achieving the lowest mean absolute error (MAE) while balancing computational efficiency.

A first-stage Butterworth filter of order 4 was applied to retain relevant frequency components (0.5–20 Hz), targeting the signal's physiological range while attenuating noise [12]. Following this, a second-stage Bessel filter of order 3 was applied to preserve the waveform shape and phase information, providing smooth and accurate signal transition [13]. It is worth mentioning that no other motion artifact or respiration removal techniques were applied to the signal. Figure 2 shows the raw and the filtered signal.

Subsequent to filtering, the following steps were performed sequentially:

1. Each signal is split into non overlapping epochs of 2.2 second(sec) and since the signal is of 2.7 min after pruning of 1.5 sec from each end so we obtained 74 segments for each subject.

2. The mean value was subtracted from each segment of the signal to center the signal around zero.

3. Each segment was autocorrelated to identify periodic components corresponding to heartbeats. Figure 3 shows two plots: one for each of the correlated segments and their peaks, as well as a single segment with peaks for an SR subject.

4. Peaks were identified using two criteria: the number of maximum peaks in each segment and the minimum distance between peaks.

5. Segments with peaks less than the threshold criteria were discarded.

6. Average time interval across all segments between the first two Aortic Valve Opening (AO) peaks was calculated to find the HR of each subject. The difference between the indices of these first two peaks of each autocorrelation window gives the time interval in samples which is later divided by sampling frequency to convert this interval into seconds. Figure 3B shows time interval between the first two peaks of a segment for a subject.

After the sixth step the Estimated HR beats per minute (BPM) was compared with the actual BPM. Since the dataset involves two main categories of datasets SR and AF so the analysis of both was carried out separately.

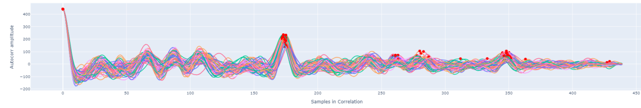
III. RESULTS

This section presents the results and findings obtained from the evaluation for HR measurement. The results are represented separately for both SR and AF subjects.

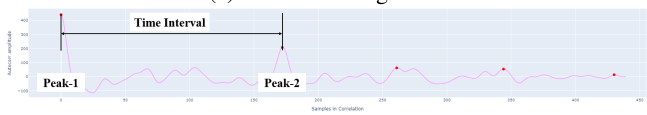
A. SR Subjects

For SR subjects, the MAE was determined to be 4.54 BPM compared to actual HR. Remarkably, around two-thirds of the participants obtained accuracy within ±5% of the actual HR, which is consistent with the AAMI recommendations for HR monitoring equipment [13]. Figure 4 shows the subjects which were within and out of range of ±5 BPM.

Further analysis showed that subjects with HRs greater than 95 and lower than 45 BPM had the largest MAE. In



(a) Correlated Segments



(b) Single Correlated Segment

Fig. 3: Part A shows all correlated segments for subject 1 Part B shows single correlated segment for subject 1 along with Time Interval Calculation between first two peaks of a segment

particular, MAE values ranged from 19-23 BPM for subjects with HRs between 110-115 BPM and 47-50 BPM.

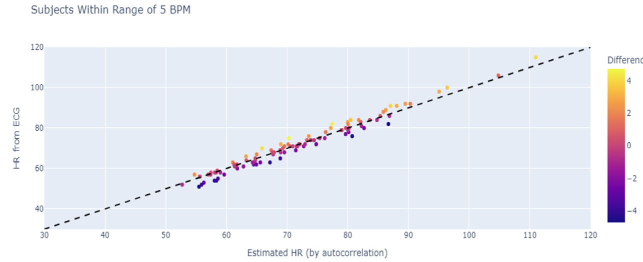
Bland Altman's plot is another tool to access the results which is employed in this study. To assess the agreement between HR measurements obtained through autocorrelation and the ECG reference standard, a Bland-Altman plot was employed which showed a mean difference of 0.13 for all the SR subjects. Figure 5 illustrates the differences between the estimated HRs (TrueHR - EstHR) plotted against their average values. The majority of the data points lie within the 96% limits, demonstrating a high level of concordance between the autocorrelation-based HR estimation and the ECG reference, particularly for subjects in SR.

B. AF Subjects

The MAE for AF subjects was 15.7 BPM which is not highly satisfactory. Around one third of the subjects obtained accuracy with in ±5% of the actual HR. Figure 6 shows the subjects which were within and out of range of ±5% BPM. Further investigations showed that almost one third of the subject's actual HR was between 170-100 BPM. The highest MAE ranged between 70-20 for 90% of these subjects. Bland Altman's plot shows that the mean difference between the actual HR and calculated HR for AF subjects is 11.87 as compared to 0.13 for the SR subjects. Figure 7 shows the Bland Altman's plot for AF subjects. The Bland-Altman plot for AF subjects reveals a mean difference of 11.87 BPM, signifying reduced concordance with the ECG reference compared to SR subjects.

IV. DISCUSSION

The MAE for SR subjects was 4.54 BPM. This level of accuracy is comparable to findings by Laurino et al. who obtained the accuracy of 1.88 BPM, on employing a moving autocorrelation window approach for HR estimation on BCG signal and reported good performance against ECG reference [6]. However, the number of subjects were only 10 with the mean BMI: 24.9 kg m ^{2} and their HR values varied between 50-100 BPM. All subjects in the study were SR. Similarly, Sefizarei et al. applied radar-based correlation method and obtained an MAE of 2.22 BPM after channel selection while



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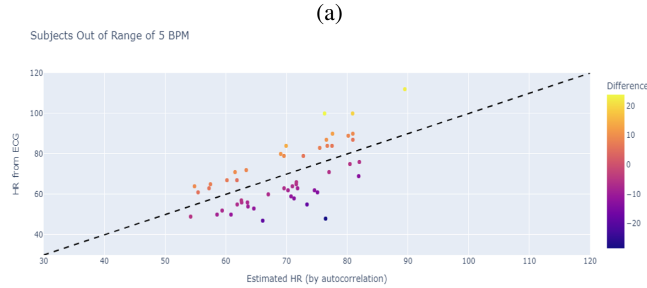


(b)

Fig. 4: SR subjects within and out of range of ±5 BPM range

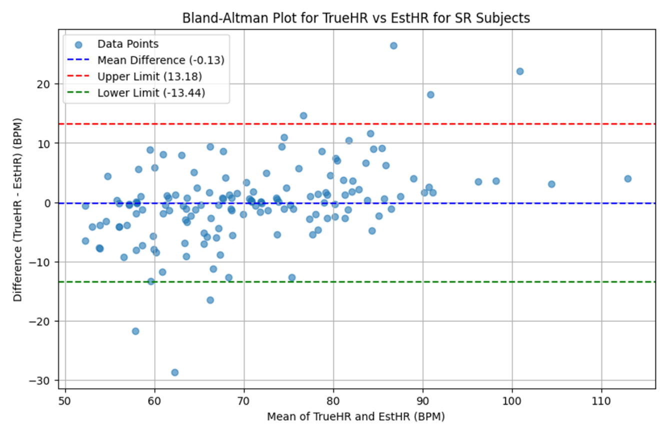
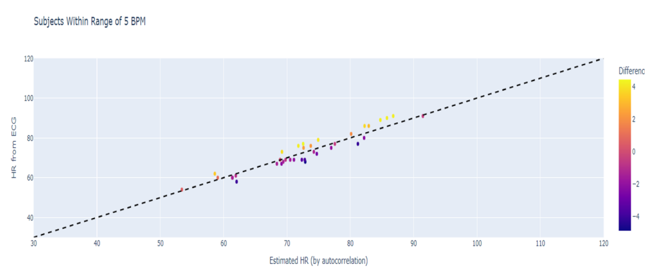


Fig. 5: Bland-Altman Plot for SR Subjects



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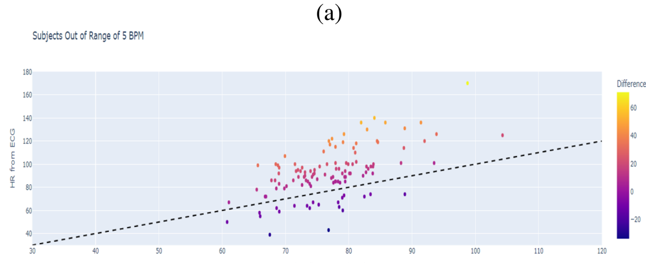

(b)

Fig. 6: AF subjects within and out of range of ±5 BPM range

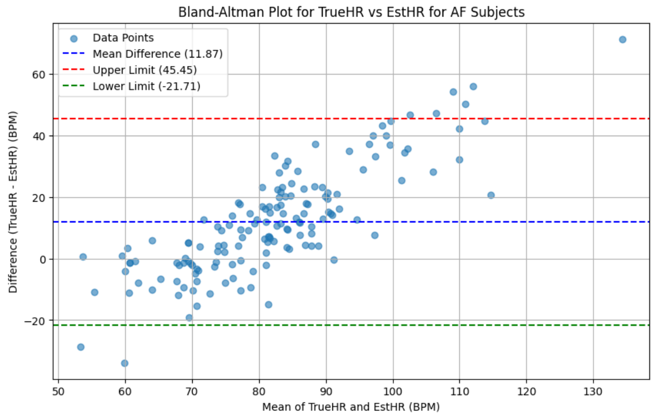

Fig. 7: Bland-Altman Plot for AF Subjects

without axis selection the accuracy remained 5.59 BPM for 15 subjects with mean BMI of 28 kg m^2. This study included subjects with arrythmia as well [14].

V. CONCLUSIONS

The proposed autocorrelation-based HR estimation method was evaluated, demonstrating an MAE of 4.54 BPM for SR subjects and 15.7 BPM for AF subjects compared to ECG-derived HRs. This method uniquely avoids the need for individual heartbeat detection, making it a robust and practical baseline estimator in scenarios lacking reference ECG data. Its simplicity and reliability suggest strong potential for non-invasive HR monitoring applications. However, some limitations of the study must be noted, including a relatively higher error observed for subjects with extreme HRs and AF subjects, suggests opportunities for further refinement of the methodology. Future research will focus on improving HR detection accuracy in AF patients by exploring adaptive autocorrelation techniques and dynamic thresholding, as well as incorporating open datasets, diverse subject groups, and extended recording durations to validate the robustness and applicability of this approach across broader cardiac conditions.

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