Innovative non-contact r-r intervals estimation using viterbi algorithm with Squared Branch Metric (VSBM)

Win Thu Zar[1*], Hla Myo Tun[1,2], Lei Lei Yin Win[1] and Zaw Min Naing[2]

[1*]Department of Electronic Engineering, Yangon Technological University, Yangon, **Myanmar**
[2] Department of Research, Yangon Technological University, Yangon, **Myanmar**
[3] Department of Research and Innovation, Yangon, **Myanmar**

*Corresponding Author: winthuzar.iro@gmail.com
Received November 18th 2023; Revised January 09th 2024; Accepted January 19th 2024

Cite this https://doi.org/10.24036/jptk.v7i1.35623

Abstract: Non-contact heartbeat detection by using Doppler sensor is a critical component of remote health monitoring systems, enabling continuous and unobtrusive monitoring of an individual's cardiovascular health. In this paper, we reported an innovative approach for non-contact heartbeat detection using the Viterbi algorithm, leveraging the distribution of the difference of two adjacent R-R intervals (RRIs). RRIs represent the time between successive peaks in the electrocardiogram (ECG) signal and are fundamental in analyzing heart rate variability, mental stress conditions and heart diseases. Numerous non-contact Doppler sensor-based methods have been proposed for heartbeat detection, leveraging the evaluation of RRIs without physical device attachment. However, challenges arise from unwanted peaks introduced by respiration and slight body movements, even when the subject remains motionless with normal breathing. This study presented an innovative approach for selecting heartbeat peaks utilizing the Viterbi algorithm with the squared difference of two adjacent RRIs as the Branch metric (BM). Our preliminary experiments reveal that the difference between two adjacent RRIs closely follows a Gaussian distribution. Building upon this observation, we considered the Viterbi algorithm with Squared Branch Metric (VSBM) to estimate the heartbeat accurately. To assess the accuracy of our peak selection method, we conducted experiments comparing it with two existing peak detection methods: (i) Doppler output after Low-Pass Filter (LPF)-based method and (ii) Spectrogram-based method. Our results demonstrate that the proposed VSBM method is effective to detect the heartbeat accurately for each peak detection method. Furthermore, we compared the performance of "Spectrogram + VSBM" outperforms the "Doppler output after LPF + VSBM" method by the Root-Mean-Square Error (RMSE) of RRIs.

Keywords: Heartbeat detection; VSBM; RRI; Variability; Remote health

1. Introduction

Heartbeat is a critical physiological indicator reflecting an individual's health status. Notably, the variation in R-R Interval (RRI) has been identified as a valuable parameter for assessing both cardiovascular and non-cardiovascular conditions in a subject (Aram & Setarehdan, 2013; W. Hu et al., 2014; Kitagawa et al., 2022; Shi et al., 2023; Xiang et al., 2023; Yamamoto & Ohtsuki, 2021; Ye & Ohtsuki, 2021; Zar & Tun, 2022). Traditional approaches for RRI estimation involve the use of established heartbeat monitoring systems such as Electrocardiogram (ECG) or Photoplethysmography (PPG) (Tun, 2021). Despite their effectiveness, these methods necessitate physical device attachment, introducing discomfort in applications requiring prolonged monitoring (Ma & Zhang, 2004). Efforts to achieve non-contact RRI estimation have led to the exploration of

Doppler sensors (Pan et al., 2022). These sensors, designed to observe the velocity and direction of a moving target, operate by transmitting microwaves towards the target and analyzing the reflected Doppler-shifted microwaves (Batchu et al., 2017; W. Hu et al., 2014; Munoz-Ferreras et al., 2018; Ren et al., 2015). Notably, the Doppler sensor-based method for heartbeat detection eliminates the need for device attachment, distinguishing it from traditional methods such as ECG or PPG (Nosrati & Tavassolian, 2018). A key advantage lies in the ability of transmitted microwaves to penetrate through the subject's clothes, rendering the Doppler sensor-based approach non-intrusive and eliminating the requirement for the subject to disrobe (El-Samad et al., 2016; Ohtsuki & Mogi, 2016; Sekine & Maeno, 2011; Yu et al., 2018; Zou et al., 2014). Nonetheless, achieving accurate heartbeat detection presents a challenge due to the low Signal-to-Noise Power Ratio (SNR) of heartbeat components within the reflected signal of a Doppler sensor, particularly when compared to the SNRs of respiration and minor body movements. RRI estimation method based on Continuous Wavelet Transform (CWT) to address this challenge (Mogi & Ohtsuki, 2015). This method has two steps: a learning step and a test step. The learning step estimates the scale factor corresponding to the heart rate. Subsequently, in the test step, CWT is applied to the analyzed signal using the selected scale factor, generating a time-domain signal referred to as wavelet coefficients. The RRI is then estimated through peak detection within the obtained wavelet coefficients. This technique aims to enhance the accuracy of RRI estimation in the presence of challenging signal-to-noise conditions inherent in Doppler sensor-based heartbeat detection.

To extract the accurate heartbeat components, alternative heartbeat detection methods have been proposed, including those based on (i) the Viterbi algorithm (Ohtsuki & Mogi, 2016) and (ii) a spectrogram (Mogi & Ohtsuki, 2017). The Viterbi algorithm-based approach involves a series of pre-processing steps, such as filtering, applied to the received signal from a Doppler sensor. Subsequently, the Viterbi algorithm detects heartbeats by selecting peaks attributed to the cardiac cycle within the pre-processed signal. The Viterbi algorithm is utilized successively to generate maximum likelihood estimates, contributing to precisely identifying heartbeat components in Doppler sensor signals (Ohtsuki & Mogi, 2016). Nevertheless, the presence of respiration and slight body motions may obscure the components of the heartbeat (Wang et al., 2013). A spectrogram-based method has been proposed to address this challenge and enhance the accuracy of heartbeat detection (Mogi & Ohtsuki, 2017). This method capitalizes on the observation that the spectrum associated with each heartbeat manifests in two frequency bands: from 8 Hz to 50 Hz and from -50 Hz to -8 Hz, where the influences of respiration and small body motions are minimal. Specifically, the spectrogram-based approach integrates the spectra attributed to heartbeats across a spectrogram. Subsequently, it estimates the RRI by identifying peaks within the combined spectrum (Yamamoto et al., 2018). It is noteworthy, however, that undesired peaks may emerge within the integrated spectrum, potentially leading to incorrect peak detection.

In an attempt to address these challenges, the authors proposed a wavelet-transform-based peak detection method (Li & Lin, 2018) for rapid heart rate detection using a 5.8 GHz Continuous Wave (CW) Doppler radar with 3-5 s data lengths. This method distinguishes respiratory harmonics from the heartbeat signal by examining the peak properties of the combined wavelet frequency spectrum (Yang et al., 2021). However, the limited 3-5 s data length may lead to incorrect peak detection. Given the considerations from the discussions mentioned above, a clear need arises for an improved and more accurate peak selection method for heartbeat detection. To estimate the RRI that relies on zero crossings of the time-domain signal obtained through various signal processing techniques, such as CWT and Ensemble Empirical Mode Decomposition (EEMD) (X. Hu & Jin, 2016). EEMD is particularly adept at decomposing received signals, even in the existence of additive white Gaussian noise, into Intrinsic Mode Functions (IMFs). However, the challenge lies in selecting optimal IMFs for signal reconstruction among all decomposed IMFs. In contrast to RRI measurement methods based on ECG (De Chazal & Reilly, 2006; Islam et al., 2012), this conventional method estimates RRI through zero crossing detection of the received signal, introducing potential errors.

In a recent study (Tomii & Ohtsuki, 2015), the authors achieved enhanced RRI estimation accuracy compared to existing heartbeat detection methods using a Doppler sensor coupled with Wavelet Transform, specifically incorporating scale factor learning to accommodate situations involving small body movements. This approach demonstrated improved accuracy in estimating the scale factor corresponding to the heart rate, even in tiny body motions. However, challenges arise as the scale factor exhibits temporal variations, mainly when small body movements occur. The deformations in waveform caused by these movements may compromise the accuracy of the scale factor estimation, potentially leading to incorrect peak detection. A novel approach to heartbeat detection involves the utilization of the Viterbi algorithm. This method identifies candidate peaks attributed to heartbeats within the low-pass filtered signal. The algorithm operates by computing Branch Metric (BM), assuming that RRIs exhibit nearly equal intervals during specified periods post-low-pass filtering. Nonetheless, it is crucial to acknowledge that RRIs may undergo substantial variations over time. This temporal variability can significantly impact the algorithm's performance, necessitating careful consideration in calculating BM.

This study introduces an innovative non-contact peak selection method for more precise heartbeat detection than the traditional heartbeat detection method, leveraging the Viterbi with Squared Branch metric (VSBM). This is because the transition from the traditional to non-contact RRI estimation represents a significant advancement in healthcare monitoring, offering improved patient comfort, reduced interference, and enhanced versatility in monitoring respiratory rates across diverse scenarios. Addressing the challenge of unwanted peaks in the pre-processed signal caused by respiration and minor body motion, we identify the difference distribution between two adjacent RRIs, which can be well-approximated by a Gaussian distribution with a zero mean. Building on this observation, the BM is defined as the squared difference of two adjacent RRIs. Subsequently, the VSBM is applied to two conventional heartbeat detection methods: (i) Doppler output after Low-Pass Filter (LPF)-based peak detection method (Mogi & Ohtsuki, 2017) and (ii) Spectrogram-based peak detection method (Ohtsuki & Mogi, 2016). This application aims to select the most possible set of peaks from the candidate peaks. To assess the accuracy of the targeted method in heartbeat detection, experiments were conducted with eight healthy subjects (age: 20-30 years old) in four scenarios where the subject was (i) sitting, (ii) typing, (iii) lying-left, and (iv) lying-up, respectively. The experimental results mention the effectiveness of the "VSBM" method in detecting peaks attributable to the heartbeat across diverse scenarios. This approach showcases the promising potential for enhancing the accuracy of non-contact heartbeat detection, contributing to the advancement of remote health monitoring systems.

Furthermore, our study demonstrates that the combined approach of "Spectrogram + VSBM" outperforms the performance of the "Doppler output after LPF + VSBM" method, specifically in terms of reducing the Root-Mean-Square Error (RMSE) of RRIs. This comparison observes valuable insights into the effectiveness of different combinations in optimizing the accuracy of non-contact heartbeat detection methods. This paper contributes to the field in two primary ways: (i) by identifying the probability density function of the difference between two adjacent RRIs and (ii) by introducing a peak selection method utilizing the VSBM based on the probability density of the difference between two adjacent RRIs. These contributions enhance our understanding of non-contact heartbeat detection methodologies, offering potential advancements for remote health monitoring systems.

The structure of this paper is as follows: Section II provides the material and methods. Section III presents the experimental results and their evaluation, shedding light on the performance and efficacy of the introduced methodology. Finally, in Section IV, we offer concluding remarks summarizing the essential findings and potential implications of our study in non-contact heartbeat detection using the VSBM based on the probability density of the difference between two adjacent RRIs.

2. Material and methods

In this section, aiming for enhanced accuracy in heartbeat detection, we introduce an innovative method for peak selection using the VSBM, defined as the squared difference between two adjacent RRIs. Through a series of experiments, we substantiate the observation that the distribution of the difference between two adjacent RRIs closely conforms to a Gaussian distribution. Building upon this empirical finding, we formulate the BM as the squared difference of two adjacent RRIs and articulate our proposed method's algorithm. This approach is designed to provide a more robust and precise means of identifying peaks associated with the heartbeat, contributing to the advancement of non-contact heartbeat detection methodologies. In order to collect the heartbeats, the 24 GHz Doppler sensor is used in this experiment. The specifications of the Doppler sensor used are detailed in Table 1.

During the experiments, the Doppler sensor system operated at a carrier frequency of 24 GHz, with a transmission power set to 1 mW. The 24 GHz Doppler sensor utilized in our experiments is depicted in Figure 1 (a). The experimental setup for the sitting scenario is illustrated in Figure 1 (a). The subject sat comfortably on a chair and Doppler sensor is positioned 1 meter away from the subject's chest or upper abdomen in the sitting position. The sampling frequency was initiated at 1 kHz, and the relevant experimental parameters are provided in Table 2. In the experiments of typing, the subject sat at a desk simulating the typing the computer keyboard and the Doppler sensor is placed on the subject's chest or upper abdomen while he/she engages in typing activities. In case of lying-left action, the subject lied on the left side in a lateral recumbent position and the sensor is positioned on the left side of the subject's chest. For the lying-up position, the subject lied on their back in a supine position and the sensor is placed on the chest or upper abdomen while the subject is lying in the supine position. In the typing and lying scenario, the distance ($\square_0$) between the Doppler sensor and the subject's chest was maintained at 30 cm.

The radar's height was set at 80 cm, and the experiments were conducted with eight healthy subjects age from 20 to 30 years old who has no cardiac or sleep-related diseases. The information relevant to the Subject's characteristics before the experiment is shown in Table 3. Each case had an observation period of 120 seconds. To acquire the actual RRIs of the reference signal, the subject was equipped with an ECG device in our experiment.

Table 1. The specification of a Doppler sensor

Parameter	Value
Modulation type	Unmodulated continuous-wave
Carrier frequency	24 GHz
Sampling frequency	1 kHz
Transmission power	1 mW

Table 2. Experimental parameters

Parameter	Value
Subject's action	(i) sitting, (ii) typing, (iii) lying-left and (iv) lying-up
Distance d_0	1 m in the case (i), 30 cm in the cases (ii), (iii), and (iv)
Height of sensor	80 cm
Number of subjects	Eight person
Observation period	120 seconds

Table 3. Information relevant to the subject's characteristics before the experiment

Subjects	Age	Gender (M/F)	BMI	Medical condition
A	20	M	28.7	Normal
B	25	M	24.2	Normal
C	23	M	23.4	Normal
D	30	F	23.9	Normal
E	20	M	22.8	Normal
F	23	F	23.3	Normal
G	22	F	23.4	Normal
H	21	M	22.5	Normal

(a) (b)

Figure 1. (a) The 24 GHz Doppler sensor and (b) The experimental setup in the case of sitting

3. Results

Distribution of the difference between two adjacent RRIs

In this section, we conduct experimental evaluations on the difference distribution between two adjacent RRIs using ECG data. The difference between two adjacent RRIs is expressed as

$$dRRI_i = RRI_{i+1} - RRI_i \tag{1}$$

where i is the index of RRI. RRI_i is the RRI at an observation time i. RRI_{i+1} is the adjacent RRI. The distribution of the difference between two adjacent RRIs, as measured with ECG, in scenarios such as (i) sitting, (ii) typing, (iii) lying-left, and (iv) lying-up, respectively in Figures 2-5. The red line in each figure represents the approximated Gaussian distribution of the difference of two adjacent RRIs.

The results indicate that the difference between two adjacent RRIs can be effectively modelled by a Gaussian distribution with a zero mean across various subjects and scenarios. Leveraging this empirical observation, we propose a method for peak selection related to heartbeat, employing the VSBM. This methodology capitalizes on the consistency of the Gaussian distribution with zero means, offering a robust foundation for precise and reliable peak selection in non-contact heartbeat detection.

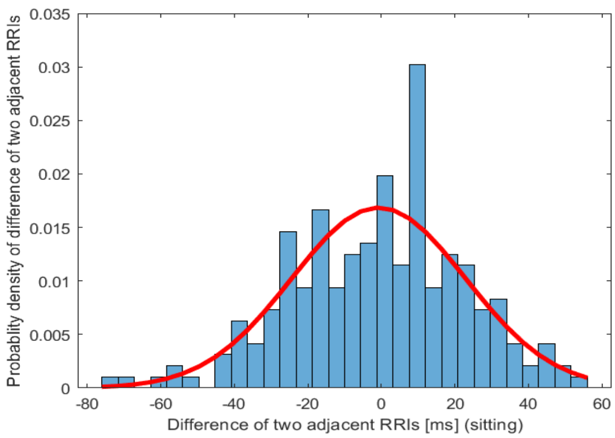

Figure 2. The distribution of the difference of two adjacent RRIs when a subject is sitting

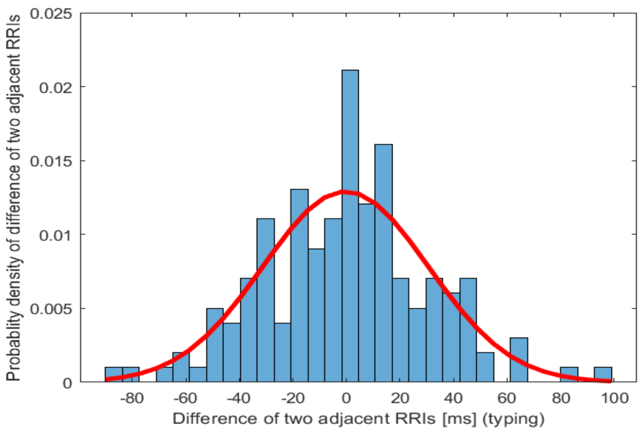

Figure 3. The distribution of the difference of two adjacent RRIs when a subject is typing

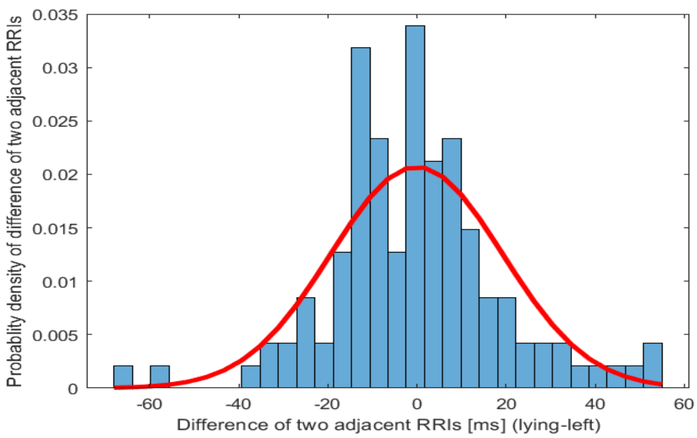

Figure 4. The distribution of the difference of two adjacent RRIs when a subject is lying-left

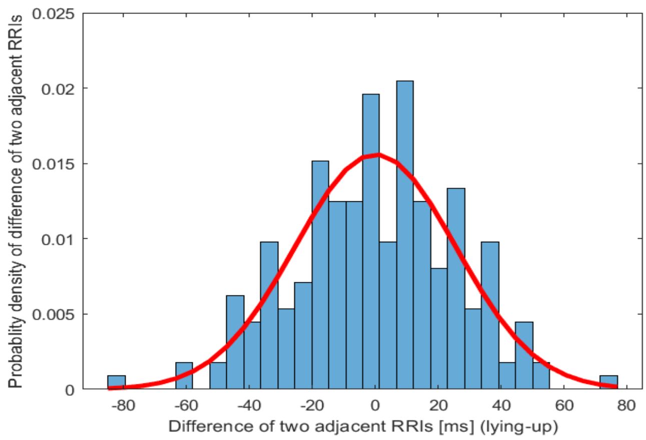

Figure 5. The distribution of the difference of two adjacent RRIs when a subject is lying up

Peak selection using VSBM

In this stage of our methodology, we apply the VSBM method to two conventional peak detection techniques, including (i) Doppler output after Low-Pass Filter (LPF)-based peak detection method (Ohtsuki & Mogi, 2016) and (ii) Spectrogram-based peak detection method (Mogi & Ohtsuki, 2017). The conventional method I is a Doppler output after LPF that represented the heartbeat detection after low-pass filtering, and the BM is calculated as the difference between an estimated average value of RRI over the observation period and an interval between two candidate R-peaks. The conventional method II is a Spectrogram-based peak detection method that involved heartbeat detection based on the spectrogram, and identifying frequency components that may correspond to heartbeats by selecting frequency bands in the spectrogram are extracted, and the low-frequency component of respiration using a band-pass filter is eliminated.

Unlike the two conventional methods, our proposed peak selection method is employed with BM, leveraging the Gaussian distribution of the difference between two adjacent RRIs to identify a set of peaks related to heartbeats from the candidate peaks. Initially, we determine the RRIs for all combinations of R-peaks within the observation periods, forming the set of RRIs (SRRI=$\{RRI_1, RRI_2, \ldots, RRI_N\}$, where N is the number of RRIs over the observation period). Figure. 7 illustrates an example of detecting candidate peaks and considering the difference between two adjacent RRIs. In this depiction, specific peaks correspond to heartbeats, while others are attributed to respiration and minor body motions. Let RRI_i represent the RRI at an observation time i and RRI_{i+1} denote the adjacent RRI. In order to estimate a combination of differences in adjacent RRIs, we considered the difference between two adjacent RRIs, $S_i=|RRI_{i+1}-RRI_i|$. Now, we have the set of S_i defined as $X_j=\left\{S_1, S_2, S_3, \ldots, S_{M_j}\right\}$, where M_j is the number of estimated RRIs in the set X_j. It is crucial to note that the number of peaks in each set may vary based on the combinations of peaks. We estimate a combination of differences in adjacent RRIs that maximizes the probability of the set of peaks.

$$\hat{X} = \arg\max_{X_j} P\left(X_j\right) \tag{2}$$

where $P\left(X_j\right)$ can be expressed as

$$P\left(X_j\right)=\prod_{i=1}^{M_j} P\left(S_i\right) \tag{3}$$

where $P(S_i)$ is the probability of the difference of two adjacent RRIs as $S_i=|RRI_{i+1}-RRI_i|$, is considered to estimate a combination of the difference of two adjacent RRIs. Equation (3) can be expressed using the log-likelihood function as (4).

$$\hat{X}=\arg\max_{X_j} \ln P\left(X_j\right)=\arg\max_{X_j} \sum_{i=1}^{M_j} \ln P\left(S_i\right) \tag{4}$$

As highlighted in the preceding section, our observation revealed that the probability density of the difference between two adjacent RRIs could be effectively modelled by a Gaussian distribution with a zero mean. Consequently, we approximate the probability $P(S_i)$ as:

$$P\left(S_i\right)=\frac{1}{\sqrt{2\pi\sigma^2}} \exp-\left(\frac{S_i^2}{2\sigma^2}\right). \tag{5}$$

where σ^2 is the variance of the difference of adjacent RRIs. We have the following equations by substituting (5) into (4).

$$\hat{X}=\arg\max_{X_j} \sum_{i=1}^{M_j} -S_i^2=\arg\min_{X_j} \sum_{i=1}^{M_j} S_i^2 \tag{6}$$

Building upon the equation mentioned above, the maximization of the log-likelihood function is achieved by minimizing the sum of the squared difference between two adjacent RRIs. Consequently, we define BM as the squared difference of two adjacent RRIs.

$$BM=\left|S_i^2\right|. \tag{7}$$

Based on the finding of the probability density of the difference between two adjacent RRIs, the BM is established as the squared difference of two adjacent RRIs.

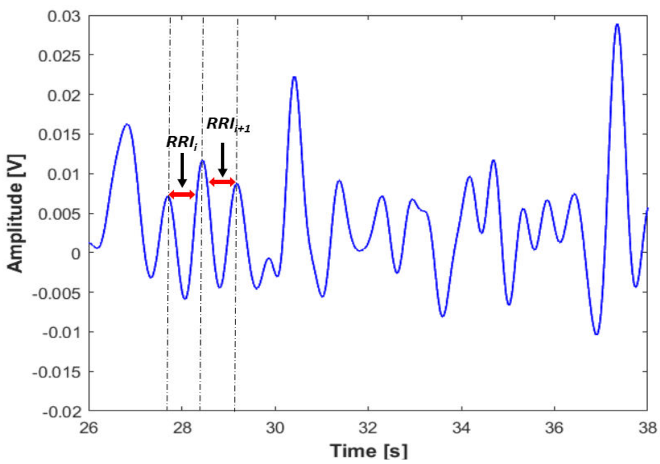

Figure 6. An example of the detection of candidate peaks

4. Discussion

We conducted several experiments to assess the accuracy of our proposed peak selection method. In order to assess the accuracy of RRI detection, we compute the RMSE between the RRIs derived from the ground-truth signal obtained via ECG and the estimated RRIs using the VSBM. The average RMSE is determined by:

$$\overline{RMSE} = \sqrt{\frac{1}{K}\sum_{j=1}^{K}\left|RRI_{VSBM}(t_j) - RRI_{ECG}(t_j)\right|^2}\ , \tag{8}$$

where K represents the number of RRIs over the observation period, and t_j is the time when the j^{th} peak appears. RRI_{VSBM} is the estimated RRI using the VSBM, and RRI_{ECG} is the ground-truth value of RRI. In our evaluation, to compare the average RMSE of RRIs, we applied the VSBM to two conventional heartbeat detection methods: (i) Doppler output after Low-Pass Filter (LPF)-based peak detection method (Ohtsuki & Mogi, 2016) and (ii) Spectrogram-based peak detection method (Mogi & Ohtsuki, 2017).

These evaluations aim to comprehensively compare the performance of the proposed VSBM across various peak detection techniques. Figure. 8 shows a comparative analysis of the average RMSE of RRIs when utilizing the VSBM in two conventional methods where the subjects were sitting, typing, lying left, and lying up, respectively. According to the experimental findings, irrespective of the cases and within each peak detection method, the proposed VSBM consistently achieves superior accuracy in peak selection compared to the peak detection in two conventional methods. This outstanding performance can be observed to the proposed VSBM being formulated based on the distribution of the difference between two adjacent RRIs; a Gaussian distribution well approximates a probability density function.

Furthermore, our observations reveal that the "Spectrogram + VSBM" combination attains the highest peak detection accuracy compared to the "Doppler output after LPF + VSBM". This heightened accuracy results from defining the BM based on the probability density of the difference between two adjacent RRIs, which is effectively modelled by a Gaussian distribution. Integrating this BM with the spectrogram-based method enhances peak detection accuracy, outperforming the other methodologies in the evaluation.

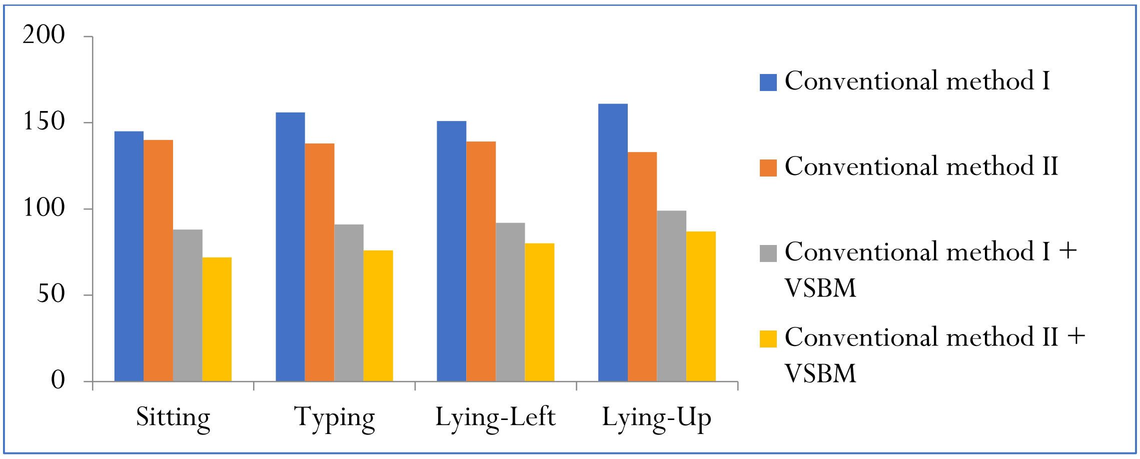

Figure 7. Comparison of average RMSEs of RRIs [ms] for the two conventional peak detection methods using VSBM

According to the experimental studies in this work, the performance of the estimation is acceptable for real world applications. This work is a novel study by comparing with some similar works and the results on this study are very much acceptable for utilization. The research gap is quite small because of the comparative studies in Figure 7.

5. Conclusion

In conclusion, the innovative approach presented in this study for non-contact R-R intervals estimation using the Viterbi algorithm with Squared Branch metric (VSBM) holds significant promise for advancing the field of physiological monitoring. By leveraging the Gaussian distribution under various conditions, such as sitting, typing, and lying, we have demonstrated a method that not only enhances the accuracy of RRI estimation but also addresses challenges associated with non-contact methodologies. The VSBM has proven to be a robust strategy for extracting reliable RRIs from non-contact physiological signals. This innovation has the potential to revolutionize remote monitoring applications, enabling unobstructive and continuous assessment of cardiac activity in various setting. The study's findings not only showcase the efficiency of the proposed methodology but also underscore the significance of continuous innovation in non-contact physiological monitoring. As we move towards a future where remote healthcare plays an increasingly pivotal role, the development and refinement of such algorithms become imperative. It is important to acknowledge the limitations of the current study, such as the need for further validation in larger and more diverse populations. Future research could explore the integration of additional features or sensor modalities to enhance the algorithm's performance further.

Finally, the non-contact RRI estimation using VSBM represents a valuable contribution to the evolving landscape of physiological monitoring. This research promotes the way for future advancements in remote healthcare, opening new possibilities for obstructive and accurate cardiac monitoring, with potential implications for preventive care, telemedicine, and personalized health management.

Author contribution

Win Thu Zar: data collection, data analysis, methodology, experimentation, draft preparation, correspondence. Hla Myo Tun: supervision, methodology, reviewing and editing. Lei Lei Yin Win: supervision, validation. Zaw Min Naing: conceptualization, methodology and validation.

Funding statement

This research received no specific research grant from any funding agency in all sectors.

Acknowledgements

The authors would like to acknowledge the Ohtsuki lab under the Department of Information and Computer Science at Keio University for providing the research data.

Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper, and they have not received any research grants from funding agencies or financial support for attending symposia.

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