A Graph-based Method for Interbeat Interval and Heart Rate Variability Estimation Featuring Multi-channel PPG Signals During Intensive Activity

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Abstract—**Inter-beat-interval (IBI) and heartrate variability (HRV) is important for numerous health monitoring applications. Although photoplethysmogram (PPG) sensors in wearables enable measurement of IBI, motion artifacts significantly impact the ability to accurately measure IBI. In this paper, we design a graph-based method to estimate IBI from motion-corrupted multi-channel PPG. We extract candidate heartbeats from noisy signals and leverage continuity in heartbeats to model them as a directed acyclic graph. IBI estimation is then modeled as a shortest-path problem in this graph. Our algorithm achieves percentage error of 4.33% and correlation of 0.94 for IBI estimation in motion-contaminated segments of PPG signals.**

Keywords— Multi-channel Signal; Convex Function; Heart Rate Variability; Interbeat Interval; Motion Artifacts

I. INTRODUCTION

Continuous measurement of heartrate variability (HRV) through non-invasive wearables provides vital information regarding health status [1]. HRV is the measurement of variation in time intervals between consecutive heart beats (i.e., interbeat intervals, IBIs) and serves as a crucial indicator in healthcare research as well as in clinical practice. For example, HRV is applied to evaluate the cognitive load in surgeons and drivers [2, 3]. In clinical practice, HRV represents the activity of the autonomic nervous system, and low HRV has been shown to be associated with a higher risk of all-cause death and cardiovascular events [4, 5].

Photoplethysmogram (PPG) signal measured by wearable sensors is a convenient tool for continuous IBI and HRV monitoring in daily life, as an alternative to the standard electrocardiography (ECG) [1]. PPG could be used to estimate a variety of important physiological information, such as blood oxygen saturation (SpO2), average heart rate (HR), respiratory rate (RR) [6], and blood pressure (BP) [8]. PPG-based techniques have shown great performance for HRV monitoring in stationary conditions. High level of agreement was reported between IBI/HRV parameters derived from wearable-based PPG sensors and ECG signals as ground truth [1]. PPG signals, however, are susceptible to motion artifacts. The performance of PPG-based IBI estimation techniques significantly deteriorates as the level of physical activity increases, which is a more challenging problem than attaining average HR. Average HR exhibits more consistency over time compare to noise and HRV. Therefore, it is easier to separate average HR out from noisy PPG, while estimating HRV is extremely challenging during intensive physical activity. Hence, there is an unmet need to improve this performance for health monitoring applications.

In this study, IBI and HRV parameters are obtained from noisy multi-channel PPG signals in the presence of motion artifacts. A characteristic weighted graph with convex weight assignment function is proposed to model multi-channel PPG signals. Since the end of one heartbeat is the beginning of the next heartbeat, a directed acyclic graph is constructed where nodes represent the feature candidates (*i.e.*, heartbeats) and edges represent candidate IBIs. Shortest path algorithm is then used to remove noisy feature candidates and calculate accurate IBIs and HRV.

This article makes the following contributions:

- Development of a characteristic weighted graph to model multi-channel PPG signals.
- Formulation of a convex penalty function leveraging power function and distance function to optimize weight assignment in the shortest path algorithm to attain high accuracy IBI estimation.

II. RELATED WORK

In past decades, research about HR estimation for wearable PPG signals have quite matured. Some studies have shown highly accurate estimation of average HR during intensive physical activity using single-channel PPG, such as TROIKA [10], WFPV [11] and particle filtering [12]. Other studies have attempted to leverage multi-channel PPG for accurate average HR estimation [13, 14]. Although, above techniques attain accurate HR using single-channel and multi-channel PPG signals, they haven't provided techniques for HRV and IBI estimation that are more challenging to estimate from PPG. There were studies providing IBI and HRV parameters estimation from wrist-worn PPG sensors in post-anesthesia patients [7, 15]. Although they have shown small absolute errors of IBI and HRV parameters, their PPG signals did not suffer from motion artifacts distortion. One study has shown medium-high (0.74 - 0.88) correlation between wrist-worn PPG sensors and ECG in HRV parameters at rest condition, but the correlation was lower (0.42 - 0.67) while subjects were talking [16]. However, these studies eliminated all PPG signals that were corrupted with motion artifacts from their analysis. The IBI estimation in a recent study, which utilized single-channel PPG, presented a medium-high (0. 819 to 0.886) correlation between the PPG sensors and ECG during intense physical activity but no percentage error was reported [9].

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III. Method

A. Dataset and Feature Extraction

We use the dataset from the 2015 IEEE Signal Processing Cup in which two-channel PPG signals (PPG1 and PPG2) and one-channel ECG signal were recorded synchronously from 12 subjects aged 18 to 35 at a sampling rate of 125 Hz [10]. Every subject ran on a treadmill with changing speeds while wearing a wrist-worn dual PPG sensor with green LEDs and wet ECG electrodes over the chest. Both ECG and PPG signals are up-sampled from 125 Hz to 500 Hz. Then PPG signals are preprocessed with a band-pass Butterworth filter with a cutoff frequency of 0.7 Hz and 15Hz. ECG signals are filtered with a high-pass Butterworth filter with a 0.5 Hz cutoff frequency. To make the R-peaks more prominent and robust for peak detection in ECG, a continuous wavelet transform is applied to ECG signals, which are regarded as the ground truth for the performance evaluation [17].

Systolic peaks, maximum slopes, and onset points are important morphological features in PPG signals that could be used for IBI estimation [8]. Figure 1 shows the process of extracting these features, which are regarded as candidate fiducial points in our study. First, a 5th order smoothing spline is applied on both filtered PPG signals to have smoother curves. Then, a peak detection algorithm detects the local maxima of PPG and ECG signals to obtain the systolic peak candidates of PPG and R-peak candidates of ECG, respectively. Afterwards, we use the same peak detection method to obtain maximum slope candidates from the first derivative of the PPG signal as well as onset candidates from the second derivative of the PPG as shown in Fig. 1A. For a specific feature, the time difference between two candidate fiducial points is considered as a candidate IBI. The presence of motion artifacts, however, produce many false fiducial points which impact the accuracy of IBI estimation greatly.

B. Graph Modeling and Shortest Path Calculation

After extracting aforementioned features, we generate a weighted graph to represent the candidate heartbeats and IBIs. The graph is then used to find the real IBIs and filter out the ones induced by motion artifact.

a) Multi-Channel Graph Construction

We construct a directed acyclic graph, where the vertices represent the candidate fiducial points and edges represent candidate IBIs. Since the end of each heartbeat is the beginning of its next heartbeat and they are continuous in time

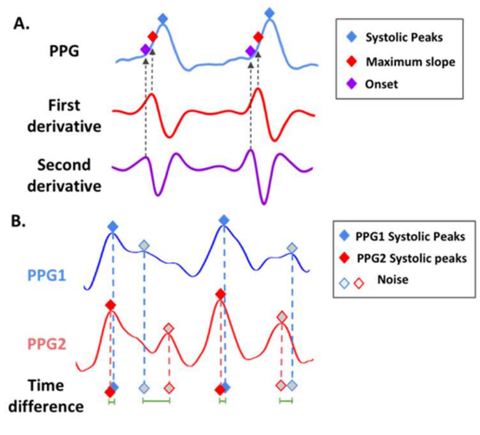

Figure 1. (A) Feature extraction process (B) Observation of time difference comparing fiducial points from true peaks and noise.

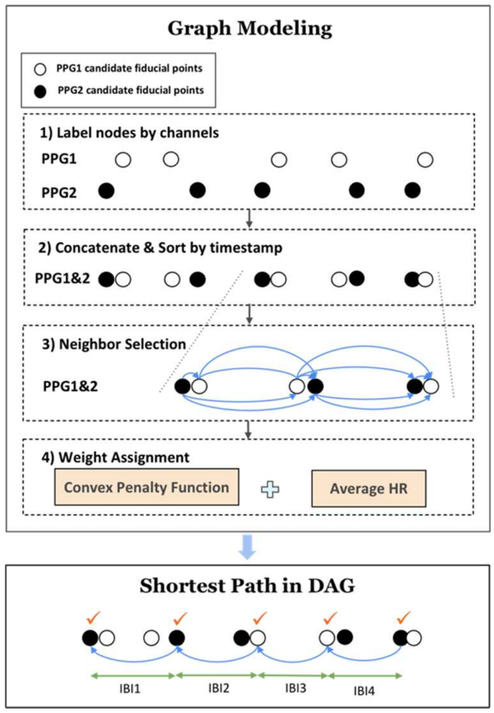

Figure 2. Overview of multi-channel PPG graph model

domain, the shortest path is used to select the fiducial points that correspond to true heartbeats. We observe that the corresponding fiducial points of true heartbeats between PPG1 and PPG2 have smaller time intervals than those false fiducial points induced by noisy signals as shown in Fig. 1B. Therefore, integrating the two PPG channels improves the capability of our technique in selecting true heartbeats through the shortest path algorithm. The multi-channel graph model is constructed by the following steps, as shown in Fig. 2. We first label vertices from different channels with colors. The color indicates which PPG channel the candidate fiducial point belonged to and it helps determine the contribution of each channel in the final IBI path. Then, we concatenate vertices from two channels and sort them by timestamps. Vertices are denoted as v_i, $i = 1,2,\dots,N$ and their values are equal to their timestamp. This step is applied on systolic peak, maximum slope and onset, respectively. As for the edges, we consider a time interval prior to each vertex v_i with the range of 1.5 folds of its average IBI, $(IBI_{avg})_i = 6000 \,/\, (HR_{avg})_i \ [ms]$where the $(HR_{avg})_i$ of each vertex v_i is equal to the average heartrate of the closest 8-second PPG window estimated by WFPV algorithm [11]. Vertices that fall within this interval are regarded as neighbors of the vertex v_i and they are linked with edges.

b) Weight Assignment by Convex Penalty Function

We assign weights to each edge based on their deviation from the average IBI. An effective penalty function for assigning weights to the edges of the graph would be critical for the shortest path algorithm to obtain the correct IBI path. For example, the exponential penalty function shown in (1) was proposed in a previous study to generate a similar graph:

$$w_{ij} = e^{\min\left(\left|(IBI_{avg})_i - \varepsilon - e_{ij}\right|, \left|(IBI_{avg})_i + \varepsilon - e_{ij}\right|\right)} \tag{1}$$

where e_{ij} is the time difference between i'th and j'th vertex. However, if e_{ij} for an edge is within the range of $\left(IBI_{avg}\right)_i \overline{+/-}\ \varepsilon$, the weight is assigned as zero. The concept

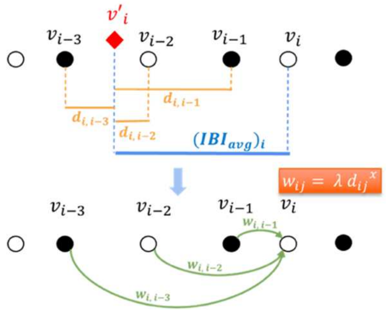

Figure 3. Weight assignment by convex penalty function

is that the distance between any pair of true fiducial points should be equal to the average IBI with a tolerance of ε [9]. However, there is no discrepancy for those vertices inside the interval and for those vertices out of the interval, the exponential growth weight of edges induces an over-penalty with enormous scale. To address these issues, we design a convex penalty function for the shortest path algorithm which is calculated through (2)-(4) and shown in Fig. 3.

$$v'_i = v_i - (IBI_{avg})_i, i = 1,2.., N \tag{2}$$

$$d_{ij} = |v_j - v'_i|, j = i-1, \dots, i-m_i \tag{3}$$

$$w_{ij} = \lambda\, d_{ij}^{\ x}, x \in \mathbb{N} \tag{4}$$

Firstly, we obtain v'_i, which represents the expected timestamp of v_i's previous vervex, by subtracting v_i by its average IBI; N is the total number of vertices in the graph. Secondly, for each v_j that is a neighbor of v_i (m_i is the total number of neighbors of vertex v_i), we calculate the distance d_{ij} between v_j and v'_i. The power function raises the d_{ij} to the power of x with a constant parameter λ, where the power x can be any natural number. We, finally, have the w_{ij} from the convex penalty function as the weight of the edge that connects v_i to neighbor v_j. Our weights of edges grow smoothly compared to the exponential penalty function. This convex property helps the shortest path algorithm reach the optimal solution and avoids potential overflow error in numerical computation.

c) *Shortest Path Calculation*

After constructing the weighted graph as explained above, we run the shortest path algorithm on this graph to select the path with the least total weight [9]. This path has the minimum total deviation, measured by our proposed convex penalty function, from the average IBI. Selected vertices on this path are regarded as fiducial points of true heartbeats and the time differences of the successive selected vertices are regarded as the estimated IBIs.

IV. Results And Discussions

A. *Interbeat Intervals Results*

We evaluate the accuracy of estimated IBIs from PPG using Pearson Correlation Coefficient (Corr) and Mean Absolute Percentage Errors (MAPE) as compared to true IBIs from ECG. We compute the MAPE using (5), where n is the number of total IBIs.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{|trueIBI_i - estimatedIBI_i|}{trueIBI_i} \times 100\right] \tag{5}$$

Table 1 shows the performance comparison between our method and the state-of-the-art [9]. We achieve correlation of 0.902, 0.931 and 0.939, and MAPE of 5.76%, 4.67% and 4.33% when systolic peak (SP), maximum slope (MS) and onset are used to estimate IBIs, respectively. Our multi-channel model shows better results for all three morphological features.

TABLE I. IBI Estimation Performance

	SP		MS		Onset	
	Corr	MAPE	Corr	MAPE	Corr	MAPE
Single-channel (PPG1)						
Our Convex Penalty Function	0.832	8.43%	0.838	8.06%	0.859	7.66%
Exp Penalty Function [9]*	0.826	8.73%	0.825	8.61%	0.829	8.83%
Single-channel (PPG2)						
Our Convex Penalty Function	0.782	10.5%	0.825	9.3%	0.844	8.48%
Exp Penalty Function [9]	0.778	10.7%	0.805	10.2%	0.812	10.1%
Two-channel (PPG1&2)						
Our Convex Penalty Function	0.902	5.76%	0.931	4.67%	0.939	4.33%
Exp Penalty Function [9]	0.879	6.94%	0.906	6.02%	0.912	5.83%
Our Best Result (PPG1&2)	0.902	5.76%	0.931	4.67%	0.939	4.33%
Aygun et al. [9] (PPG1)	0.819	n/a**	0.845	n/a	0.855	n/a

This table shows average metric over the first 12 subjects in 2015 IEEE Signaling Processing Cup.
* Our implementation in python using the exponential penalty function [9]
** n/a : not available

We also implement the single-channel model as described in [9] and compare with our two-channel model in Table 1. The table also compares our convex penalty function with that proposed in [9]. Our two-channel model outperforms both the single-channel model PPG1 and the single-channel model PPG2. The multichannel approach achieves 31.7%, 42.1% and 43.5% improvement in MAPE for systolic peak, maximum slope and onset, respectively. We also analyze the percentage of channel usage, and the results show the usage of two channels are 53.3% v.s. 46.7%, respectively, which suggests the importance of multi-channel models. Our convex penalty function has better performance than the Exp Penalty Function [9] both in the single-channel model and two-channel model. We use the 2nd power for the convex penalty function in our algorithm.

B. *Heart Rate Variability*

The estimated IBIs are used to calculate four time-domain HRV parameters, including Mean RR (*ms*), SDNN (*ms*), Mean HR(*1/min*) and STD HR (*1/min*), using pyHRV [18]. The estimated/true HRV parameters are highly correlated with range from 0.919 to 0.999 with low percentage errors.

TABLE II. HRV Parameters Performance

HRV Parameters	Our Method		Aygun et al.[9]*	
	Corr	% error	Corr	% error
Mean RR (*ms*)	0.999	0.38%	0.986	n/a
SDNN (*ms*)	0.995	5.92%	0.956	n/a
Mean HR (*1/min*)	0.998	0.65%	0.987	n/a
STD HR (*1/min*)	0.919	10%	0.860	n/a

* HRV analysis of our method is based on only the Onset feature (our best result), while HRV analysis of Aygun et al. [9] is based on fusion of three features, SP, MS and Onset.

V. Conclusion

We proposed a graph model for IBI estimation on multi-channel PPG signals collected during intensive exercise. A penalty function, the convex penalty function, was introduced to assign edge weights in the shortest path calculation. Our method, using two-channel PPGs and the convex penalty function, achieved low average percentage error of 5.76%, 4.67% and 4.33% and high average correlation of 0.902, 0.931 and 0.939 for IBI estimation through systolic peak, maximum slope and onset, respectively. The estimated/true HRV parameters were also highly correlated with low percentage errors. We also demonstrate that the two-channel PPG has better performance than the single-channel methods.

References

[1] K. Georgiou, A. V. Larentzakis, N. N. Khamis, G. I. Alsuhaibani, Y. A. Alaska, and E. J. Giallafos, “Can Wearable Devices Accurately Measure Heart Rate Variability? A Systematic Review,” *Folia Med (Plovdiv),* vol. 60, no. 1, pp. 7-20, Mar 1, 2018.

[2] T. Zhou, J. S. Cha, G. Gonzalez, J. P. Wachs, C. P. Sundaram, and D. Yu, “Multimodal Physiological Signals for Workload Prediction in Robot-assisted Surgery,” *J. Hum.-Robot Interact.,* vol. 9, no. 2, pp. Article 12, 2020.

[3] E. T. Solovey, M. Zec, E. A. G. Perez, B. Reimer, and B. Mehler, “Classifying driver workload using physiological and driving performance data: two field studies,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Toronto, Ontario, Canada, 2014, pp. 4057–4066.

[4] G. Ernst, “Heart-Rate Variability-More than Heart Beats?,” *Front Public Health,* vol. 5, pp. 240, 2017.

[5] S. C. Fang, Y. L. Wu, and P. S. Tsai, “Heart Rate Variability and Risk of All-Cause Death and Cardiovascular Events in Patients With Cardiovascular Disease: A Meta-Analysis of Cohort Studies,” *Biol Res Nurs,* vol. 22, no. 1, pp. 45-56, Jan, 2020.

[6] S. Nabavi, and S. Bhadra, “A Robust Fusion Method for Motion Artifacts Reduction in Photoplethysmography Signal,” *IEEE Transactions on Instrumentation and Measurement,* vol. 69, no. 12, pp. 9599-9608, 2020.

[7] A. Tarniceriu, J. Harju, A. Vehkaoja, J. Parak, R. Delgado-Gonzalo, P. Renevey, A. Yli-Hankala, and I. Korhonen, "Detection of beat-to-beat intervals from wrist photoplethysmography in patients with sinus rhythm and atrial fibrillation after surgery." pp. 133-136.

[8] M. Elgendi, R. Fletcher, Y. Liang, N. Howard, N. H. Lovell, D. Abbott, K. Lim, and R. Ward, “The use of photoplethysmography for assessing hypertension,” *NPJ Digit Med,* vol. 2, pp. 60, 2019.

[9] A. Aygun, H. Ghasemzadeh, and R. Jafari, “Robust Interbeat Interval and Heart Rate Variability Estimation Method From Various Morphological Features Using Wearable Sensors,” *IEEE J Biomed Health Inform,* vol. 24, no. 8, pp. 2238-2250, Aug, 2020.

[10] Z. Zhang, Z. Pi, and B. Liu, “TROIKA: A General Framework for Heart Rate Monitoring Using Wrist-Type Photoplethysmographic Signals During Intensive Physical Exercise,” *IEEE Transactions on Biomedical Engineering,* vol. 62, no. 2, pp. 522-531, 2015.

[11] A. Temko, “Accurate Heart Rate Monitoring During Physical Exercises Using PPG,” *IEEE Transactions on Biomedical Engineering,* vol. 64, no. 9, pp. 2016-2024, 2017.

[12] V. Nathan, I. Akkaya, and R. Jafari, “A particle filter framework for the estimation of heart rate from ECG signals corrupted by motion artifacts,” *Annu Int Conf IEEE Eng Med Biol Soc,* vol. 2015, pp. 6560-5, 2015.

[13] H. Lee, H. Chung, H. Ko, and J. Lee, “Wearable Multichannel Photoplethysmography Framework for Heart Rate Monitoring During Intensive Exercise,” *IEEE Sensors Journal,* vol. 18, no. 7, pp. 2983-2993, 2018.

[14] K. M. Warren, J. R. Harvey, K. H. Chon, and Y. Mendelson, “Improving Pulse Rate Measurements during Random Motion Using a Wearable Multichannel Reflectance Photoplethysmograph,” *Sensors (Basel),* vol. 16, no. 3, Mar 7, 2016.

[15] J. Parak, A. Tarniceriu, P. Renevey, M. Bertschi, R. Delgado-Gonzalo, and I. Korhonen, “Evaluation of the beat-to-beat detection accuracy of PulseOn wearable optical heart rate monitor,” *Annu Int Conf IEEE Eng Med Biol Soc,* vol. 2015, pp. 8099-102, Aug, 2015.

[16] N. Milstein, and I. Gordon, “Validating Measures of Electrodermal Activity and Heart Rate Variability Derived From the Empatica E4 Utilized in Research Settings That Involve Interactive Dyadic States,” *Frontiers in Behavioral Neuroscience,* vol. 14, no. 148, 2020-August-18, 2020.

[17] I. Romero, B. Grundlehner, J. Penders, J. Huisken, and Y. H. Yassin, "Low-power robust beat detection in ambulatory cardiac monitoring," in *2009 IEEE Biomedical Circuits and Systems Conference*, 2009: IEEE, pp. 249-252.

[18] P. Gomes, P. Margaritoff, and H. Silva, "pyHRV: Development and evaluation of an open-source python toolbox for heart rate variability (HRV)," in *Proc. Int’l conf. On electrical, electronic and computing engineering (icetran)*, 2019, pp. 822-828.