The Effect of Motion on PPG Heart Rate Sensors

Calvin Henry, Daniel Hu, Saurabh Bagchi
Purdue University
West Lafayette, IN, USA
{henry89, hu432, sbagchi}@purdue.edu

***Abstract*—As smartwatches become more commonly used for keeping track of health data, their accuracy becomes more and more important. In this paper, we investigate the accuracy of smartwatch heart rate sensors and how it depends on the movement of the wearer. Some additional steps were taken in being able to predict whether a smart watch will report an accurate heart rate based on motion using a support vector machine.**

***Index Terms*—smartwatches, wearables, heart, rate, movement**

I. Introduction

Smart wearable technology use has become increasingly prevalent over the past decade. For example, smartwatches are frequently being used as devices to measure and monitor one's heart rate. A person who has been using a smartwatch to monitor and log their heart rate can give that data to their doctor, who can potentially use it to make diagnoses. For example, Fitbit has broadened its scope from activity trackers to partner with Google Cloud so that users can safely transmit health data from their smartwatches to their doctors and their electronic medical records [1].This new source of data has the potential to lower healthcare costs by reducing in-person medical visits and detecting potential issues before they escalate [2]. Because of these higher profile use cases, the security and accuracy of the bio metric sensors on these devices is becoming increasingly important, which was one of the motivating factors behind our research.

Many smart watches use photoplethysmography (PPG) to measure heart rate which uses light to measure how much blood the heart is pumping under the surface of the skin. Even though this technology is less accurate than a medical grade electrocardiogram (ECG), smart watch manufacturers opt to use PPG in their heart rate monitors because it is far cheaper, simpler, and more portable than the electrocardiogram. In this paper, we investigate the relationship between the accuracy of the PPG sensor in smart watch heart rate monitors and movement, specifically gyroscopic speed and angular acceleration.

II. Related Work

The accuracy of smartwatch PPG monitors has long been the subject of study, with many papers that compare the accuracy of a PPG heart rate sensor on a smartwatch to an electrocardiograph. A substantial number of these studies conclude an acceptable degree of accuracy for the PPG sensor when compared with an ECG [3] [4] [5] [6]. We decided to examine whether each axis of movement had a significant impact on the accuracy of the smartwatch heart rate monitor. Ra et al. [7] uses the PPG's light intensity to classify whether or not a smart watch measurements are accurate or not. However, Tizen OS is the only mobile OS to include light intensity in their sensor data, while movement information from sensor data is available on every mobile OS. Therefore, the usage of movement to determine heart rate measurement accuracy is far more accessible to a much larger set of smartwatches and wearables.

III. Design of Experiment

A. Data Collection

We used the Huawei Watch 2 for this study, which, like many modern smartwatches, uses PPG and a Polar H10 heart rate monitor chest strap which uses an electrocardiography sensor, which acts as the ground truth data source. We created a simple Android Wear application which recorded the following information:

- Heart rate in beats per minute, with measurements being taken once per second
- Angular Acceleration in X, Y, and Z axes in m/s^2, with measurements being taken 30 times per second
- Gyroscopic speed in X, Y, and Z axes in m/s^2, with measurements being taken 30 times per second
- Timestamp

By default, the chest strap recorded heart rate in beats per minute, with measurements being taken once per second as well as a timestamp.

4 subjects were asked to wear both the watch and chest strap while doing various activities such as running, jumping, walking, resting, etc.

B. Data Cleaning and Aggregation

For each timestamp in our collected data, we had 30 angular acceleration and gyroscopic speed measurements but only one heart rate measurement. We aggregated the angular acceleration and gyroscopic speed data by taking the standard deviation of each of the 30 measurements, resulting in singular values that signified the overall amount of angular acceleration and gyroscopic speed per timestamp (see Fig. 1). As a result, we had around 6,000 data points of heart rate measurements.

We define an accuracy threshold on the smartwatch heart rate monitor as the maximum allowable difference in beats per minute between the smartwatch PPG and chest strap ECG to still be considered ”accurate”. For example, an accuracy threshold of 10 would mean that heart rates taken on both devices would have to differ by $\leq$ 10 for the smartwatch heart rate monitor to be considered "accurate" at a given timestamp. As expected, the percentage of "inaccurate" heart rate measurements went down as we increased the accuracy threshold (see Fig. 2).

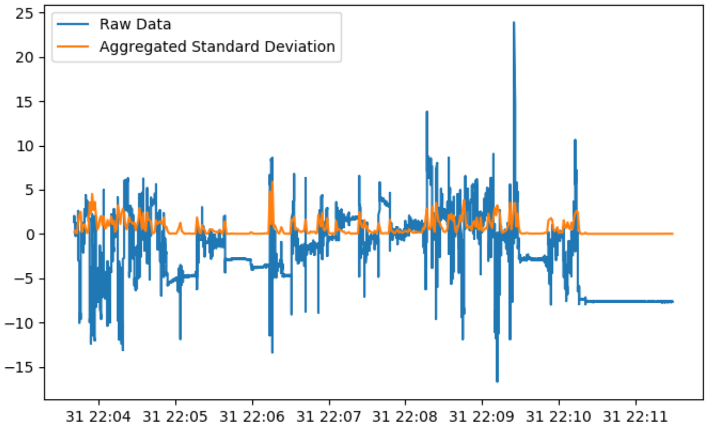

Fig. 1. Example of Data Aggregation.

IV. Analysis

We were able to simplify our problem into one of binary classification, where we could classify heart rate measurements as either "inaccurate" or "accurate" based on our defined accuracy threshold of 10. Since each heart rate measurement had associated angular acceleration and gyroscopic speed measurements, we performed a T-test and were able to conclude that gyroscopic speed and angular acceleration in all 3 axes were all contributing factors in "inaccurate" heart rate measurements. Since all the T values are relatively similar each type of acceleration had a similar affect on whether there was an error, but the linear acceleration seemed to have a slightly greater affect than the angular speed.

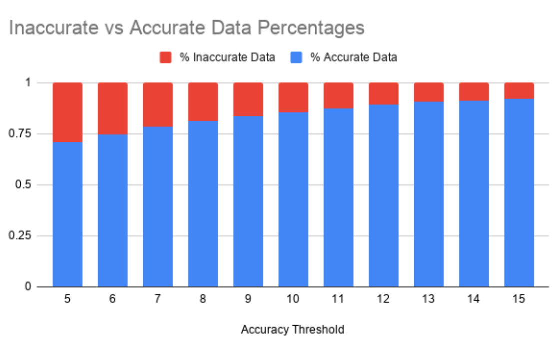

Fig. 2. Proportion of inaccurate vs accurate heart rate measurements based on accuracy threshold.

Given that all 6 measurements of movement were statistically significant, we were able to train a Support Vector Machine with a radial basis function kernel to classify a heart rate measurement as "accurate" or "inaccurate" with an accuracy of approximately 90%.

TABLE I
Movement average in m/s^2 on accurate heart rates vs inaccurate heart rates

	Accurate HR	*Inaccurate HR*	*T-Value*	*P-Value*
X acceleration	0.618	1.269	16.36	< 0.00005
Y acceleration	0.910	1.825	15.58	< 0.00005
Z acceleration	0.807	1.577	16.31	< 0.00005
X angular speed	0.469	0.889	13.63	< 0.00005
Y angular speed	0.264	0.514	13.49	< 0.00005
Z angular speed	0.314	0.692	15.01	< 0.00005

A. Conclusions and Future Work

The results of our statistical analysis and Support Vector Machine showed a clear correlation between motion and the accuracy of the heart rate sensor on the smart watch, and that it is possible to predict with high accuracy whether the heart rates measured are accurate or not. This potential could be investigated further in future works, which could attempt to filter out inaccurate heart rates.

A previous study [2] also used machine learning to predict the accuracy of a heart rate sensor with similarly high accuracy to our own by measuring light intensity of the PPG sensor when the heart rate was being measured. This could lead to investigations as to whether we can use both motion and light intensity to produce even better predictions of the accuracy of the smartwatch. Some prior work has looked at the orthogonal dimension of the vulnerability of the smart watch to large amounts of concurrent activities [8].

More robust machine learning models can also be used in the future to try and increase accuracy percentages to a point of being used reliably in commercial environments as well as the medical field where higher accuracy is more critical.

References

[1] Booten, Jen. "Fitbit And Google Team Up On Digital Health Initiative." SportTechie, 30 Apr. 2018, www.sporttechie.com/fitbit-and-google-team-on-digital-health-wearable-initiative/.

[2] Wile, Daryl J., Ranjit Ranawaya, and Zelma H.t. Kiss. "Smart watch accelerometry for analysis and diagnosis of tremor." Journal of Neuroscience Methods 230 (2014): 1-4.

[3] D. Phan, L. Y. Siong, P. N. Pathirana and A. Seneviratne, "Smartwatch: Performance evaluation for long-term heart rate monitoring," 2015 International Symposium on Bioelectronics and Bioinformatics (ISBB), Beijing, 2015, pp. 144-147.

[4] Nelson, Benjamin W, and Nicholas B Allen. "Accuracy of Consumer Wearable Heart Rate Measurement During an Ecologically Valid 24-Hour Period: Intraindividual Validation Study." JMIR mHealth and uHealth vol. 7,3 e10828. 11 Mar. 2019, doi:10.2196/10828

[5] Wang R, Blackburn G, Desai M, et al. Accuracy of Wrist-Worn Heart Rate Monitors. JAMA Cardiol. 2017;2(1):104–106. doi:10.1001/jamacardio.2016.3340

[6] Wallen, Matthew P et al. "Accuracy of Heart Rate Watches: Implications for Weight Management." PloS one vol. 11,5 e0154420. 27 May. 2016, doi:10.1371/journal.pone.0154420

[7] Ra, Ho-Kyeong, Jungmo Ahn, Hee Jung Yoon, Dukyong Yoon, Sang Hyuk Son, and Jeonggil Ko. "I Am a "Smart" Watch, Smart Enough to Know the Accuracy of My Own Heart Rate Sensor." Proceedings of the 18th International Workshop on Mobile Computing Systems and Applications - HotMobile '17 (2017): n. pag. Print.

[8] E. Barsallo Yi, A. Maji and S. Bagchi, "How Reliable is My Wearable: A Fuzz Testing-Based Study," 2018 48th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN), Luxembourg City, 2018, pp. 410-417.