Wearable Motion-Based Heart Rate at Rest: A Workplace Evaluation

Javier Hernandez, Daniel McDuff, Karen Quigley, Pattie Maes, and Rosalind W. Picard

***Abstract*—This paper studies the feasibility of using low-cost motion sensors to provide opportunistic heart rate assessments from ballistocardiographic signals during restful periods of daily life. Three wearable devices were used to capture peripheral motions at specific body locations (head, wrist, and trouser pocket) of 15 participants during five regular workdays each. Three methods were implemented to extract heart rate from motion data and their performance was compared to those obtained with an FDA-cleared device. With a total of 1358 h of naturalistic sensor data, our results show that providing accurate heart rate estimations from peripheral motion signals is possible during relatively *"still"* moments. In our real-life workplace study, the head-mounted device yielded the most frequent assessments (22.98% of the time under 5 beats per minute of error) followed by the smartphone in the pocket (5.02%) and the wrist-worn device (3.48%). Most importantly, accurate assessments were automatically detected by using a custom threshold based on the device jerk. Due to the pervasiveness and low cost of wearable motion sensors, this paper demonstrates the feasibility of providing opportunistic large-scale low-cost samples of resting heart rate.**

***Index Terms*—Physiology, wearable devices, heart rate, ballistocardiography, smartphone, smartwatch, smart eyewear.**

I. Introduction

RECENT advances in wearable technologies have created new opportunities to comfortably measure and track relevant health information during daily life [1]–[3]. In the context of cardiac monitoring, for instance, many devices incorporate cameras and LEDs to capture photoplethysmographic (PPG) signals [4] and/or electrodes to capture electrocardiographic (ECG) signals. Among all the sensor possibilities, accelerometers are arguably some of the most pervasive ones. These sensors are traditionally used to capture large and easily observable motions such as steps, walking and running (e.g., [5]–[7]), and have been widely used to assess potential source of artifacts for other measurements like PPG (e.g., [8], [9]). However, increased sensor resolution has also enabled the analysis of more subtle and difficult to observe body motions associated with cardiac activity. For instance, several recent studies (e.g., [10]–[13]) have demonstrated that commercially available wearable motion sensors can be used to capture subtle vibrations of the body associated with the beating of the heart even from peripheral body locations such as the head, the wrist, or the trouser pocket. Fig. 1 shows an example of raw signals captured from the wrist, and the pulse wave obtained after using the algorithm described in [8].

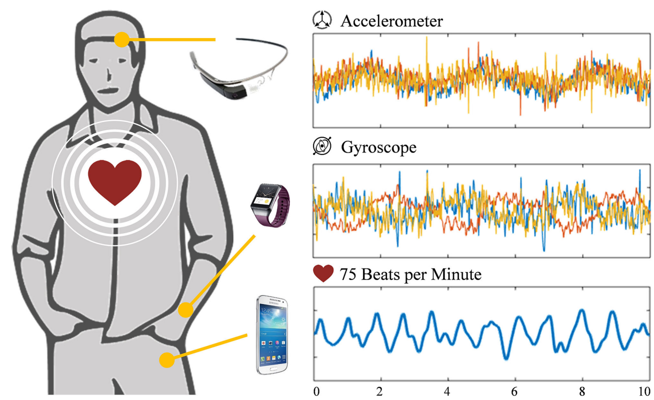

Fig. 1. Wearable motion sensors such as accelerometer and gyroscopes of readily available devices can be used to capture subtle cardiac motions during relatively *"still"* moments during the day.

In contrast to more standardized cardiac sensing methods (e.g., PPG, ECG), motion-based sensing does not require the use of electrodes or direct skin contact which is convenient when sensing children or patients with delicate skin conditions (e.g., burns, psoriasis). In addition, accelerometers can be quickly scaled due to their low cost and their low energy consumption in comparison with other sensing approaches [14]. However, the main drawback of such approach is that cardiac motions are very subtle and can be easily occluded by other body motions. Furthermore, the studies that examine cardiac vibrations tend to measure them from the chest and in laboratory settings, where the cardiac vibrations are more prominent and other body motions can be controlled. In this work, we use ECG signals to obtain the gold standard reference and focus on the study of motion-based signals to assess the possibility of

Manuscript received June 6, 2018; revised September 29, 2018; accepted October 15, 2018. Date of publication October 29, 2018; date of current version September 4, 2019. This work was supported in part by the National Science Foundation Grant NSF CCF-1029585, in part by the Google, in part by the Samsung Think Tank Team, and in part by the MIT Media Lab Consortium. *(Corresponding author: Javier Hernandez.)*

J. Hernandez, P. Maes, and R. W. Picard are with the Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139 USA (e-mail: javierhr@media.mit.edu; pattie@media.mit.edu; picard@media.mit.edu).

D. McDuff was with the Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139 USA. He is now with the Microsoft Research, Redmond, WA 98052 USA (e-mail: damcduff@microsoft.com).

K. Quigley is with Edith Nourse Rogers Memorial VA Hospital, Bedford, MA 01730, and Northeastern University, Boston, MA 02115, USA (e-mail: k.quigley@northeastern.edu).

Digital Object Identifier 10.1109/JBHI.2018.2877484

using them as a complementary approach in future devices and making health information more widely accessible.

The work presented here extends previous work and explores the possibility of estimating heart rate from three peripheral body locations (head, wrist and trouser pocket) in a naturalistic real-life environment. In particular, the main contributions of this work are: 1) we use methods that were previously developed in *"still"* laboratory conditions [10]–[12] and evaluate them for the first time using 1358 hours of real-life workplace data involving 15 participants over five regular workdays per person, 2) we demonstrate the possibility of using a motion level indicator based on the jerk of the device to effectively detect relatively *"still"* moments and provide opportunistic accurate measurements, and 3) we quantify the accuracy, frequency and distribution of accurate measurements across three body positions that are commonly used for wearable devices.

The remainder of the paper is organized as follows. First, we review relevant work on motion-based physiological sensing. Second, we review the methods that are evaluated in this work. Third, we provide details about the real-life workplace experiment. Fourth, we review previous findings in laboratory conditions and examine the results in our real-life dataset. Finally, we provide some discussion and concluding remarks.

II. Background Research

Every time the heart beats, the movement of the blood throughout the body creates tiny shifts in the center of body mass eliciting subtle body motions. These movements (a.k.a. ballistocardiographic (BCG) or seismocardiographic signals depending on the body location) were first documented in 1877 [15] and have been extensively studied since then (e.g., [16], [17]). While the original studies required a suspended mattress to magnify the subtle motions, recent improvements in electronics, such as increased sensor resolution and extended battery power, have enabled their study in less constrained settings [18]. For instance, different studies have successfully instrumented a weighing scale [19], a chair [20], and a bed mattress [21]–[24]. A common limitation of these approaches; however, is that they only work so long the person is performing certain activity at the instrumented location (e.g., standing on a weighting scale, sitting on a chair, or lying down on a bed). As a result, the potential availability of such measurements is limited to moments during the day when the device(s) is available. To address this problem, researchers have also explored the use of wearable solutions that are in close contact with the body throughout the day. For instance, several studies have explored strapping a phone around the chest and using the accelerometer sensors to monitor heart rate and breathing rate (e.g., [25]–[27]). More recently, custom-made chest-worn solutions have been developed to capture other relevant parameters such as changes in cardiac output, contractility and blood pressure (e.g., [28]–[30]). A different line of work has also explored the measurements of cardiac and respiratory vibrations from more comfortable peripheral locations. For instance, He *et al.* [31] created a custom ear-worn wearable device and demonstrated that it could also capture cardiac information from the ear. In a separate series of studies, we showed that commercially available motion sensors such as those inside head-worn [10], wrist-worn [11], [14] or smartphone devices [12] could also capture heart and breathing rates from other peripheral locations. As cardiac motions are easily affected by large motions, most of the previous studies focus on controlled settings with sedentary activities (e.g., sleeping, standing still). In an attempt to quantify how this type of measurement would generalize to more challenging real-life settings, Rienzo *et al.* [32] strapped motion accelerometers to the chest of five participants during 24 hours of ambulatory activity and then quantified the amount of *"still"* moments that would potentially qualify for cardiac analysis (the ones containing little motion). The results were promising, indicating that there were more than 100 such 5-second measurements per hour during the day and three times higher while sleeping. However, their study only captured one day each from five people, only considered chest measurements, and did not extract physiological parameters from their data. In contrast, this work considers longitudinal physiological measurement from multiple peripheral locations in a naturalistic work setting. In addition, we present actual physiological results and compare them with those provided by an FDA-cleared chest-worn biosensor.

TABLE I
Summary of Laboratory Findings

Studied Location	Best Performing Combination of Sensors	Mean Absolute Error (beats per minute)
Pocket [9]	Accelerometer	2.17
Wrist [8]	Accelerometer + Gyroscope	1.39
Head [7]	Gyroscope	0.82

III. Methods

A. Apparatus

This work considers the measurement of cardiac-induced vibrations using wearable motion sensors on three peripheral body locations (pocket, wrist and head). While smartphones and wrist-worn devices are more pervasive today than head-mounted devices, the latter location is becoming more popular with the introduction of smart headphones and glasses, as well as virtual and augmented reality headsets. In this work, we used the Galaxy S4 smartphone (Samsung, Inc.) to capture motions near the pants pocket, the Gear Live smartwatch (Samsung Inc.) to capture wrist motions, and the Google Glass (Google, Inc.) to capture head motions.

Each of the devices is equipped with both a 3-axis accelerometer and 3-axis gyroscope sensor that capture linear accelerations (meters/second^2) and rotational movements of the devices (radians/second), respectively. All three devices had sensor resolutions $<= 0.0392$ and $<= 0.0012$ for the accelerometer and gyroscopes, respectively. Furthermore, the same sensors showed mean absolute error $< = 2.17$ beats per minute in laboratory conditions (Table I). To retrieve and log motion information, we created a custom Android program that collected data at an average sampling rate of 100 Hz. However, we down-sampled the measurements to 50 Hz which provides enough resolution to capture cardiac information [10] while minimizing virtual and disk memory.

B. Gold Standard Heart Rate Measurement

To collect gold standard heart rate measurements, we used a single lead BioPatch (Zephyr Tech, Inc.) with Kendall 535 foam pre-gelled electrodes that captured electrocardiographic activity (ECG) from the torso. The device comes with proprietary algorithms to provide heart rate and confidence levels every second. The confidence values range from 0 to 100 indicating not confident to very confident, respectively. For the purpose of this study, we used only the measurements that obtained at least a 50% confidence level to evaluate the performance of the motion-based methods (around 84% of the measurements in our dataset). The BioPatch as well as the other three wearable devices were synchronized with the same clock at the beginning of each day and the information was locally stored on each of the devices.

C. Heart Rate Estimation

To estimate heart rate from peripheral cardiac signals we implemented the methods described in [10]–[12] for the head-mounted, wrist-worn and smartphone devices, respectively. These methods share similar processing steps but have tuned parameters (e.g., filter orders, frequency ranges) to capture the subtle differences at each of the locations. The main processing steps are summarized as follows:

1) Signal Pre-Processing: The motion signals (3-axis accelerometer, 3-axis gyroscope or a combination) are de-trended with averaging filters and each of the resulting filtered signals is z-scored. These steps remove small and slow-motion artifacts (e.g., gyroscope drifts) and give the same weight to each of the components, making the estimates more robust to different device orientations.

2) BCG Isolation: A band-pass Butterworth filter, with cut off frequencies specific to each of the locations, is used on each of the components to isolate and amplify the BCG motions. The minimum and maximum cut-off frequencies across devices ranged from 4 to 13 Hz; frequencies were selected to optimize performance at each body location.

3) Component Aggregation: The resulting filtered 3-axis motion data signals are aggregated with a squared root summation of the components, providing the same weight to each of the components, and making the estimations more robust to different device orientations.

4) Pulse Wave and Heart Rate Estimation: Finally, a second band-pass Butterworth filter with cutoff frequencies of 0.75 Hz and 2.5 Hz (corresponding to 45 and 150 beats per minute) is applied to extract the final pulse wave. Using this wave, the final heart rate is estimated by finding the frequency with the highest amplitude in the Fourier domain and multiplying it by 60 (beats per minute).

As in previous studies, 20-second window segments with a 75% overlap were used to divide the data streams. While more complex methods could have been developed to attempt to model and remove real-life motion artifacts, in this first real-world study we wanted to replicate the procedure applied in the laboratory experiments to establish a baseline comparison. For part of the analysis, we selected an absolute error threshold of 5 beats per minute. While this threshold is not suited to clinical applications that require highly accurate and continuous heart rate estimation, it can still be used to capture resting heart rate and overall physiological trends, and it provides comparable performance with other wrist-worn PPG devices [33].

D. Motion Level

One of the fundamental limitations when measuring BCG signals is that large motions can quickly obscure the subtle BCG motions, especially when considering locations far from the chest. To assess how the previous methods handle different levels of daily motion, we defined the following custom value:

$$\text{Motion Level} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \quad \text{where } x = \sqrt{\sum_{k=1}^{3}\left(\frac{\partial acl^k}{\partial t}\right)^2} \tag{1}$$

where N is 1000 samples (20-seconds at a sampling rate of 50 Hz), and acl^k indicates the k axis of the accelerometer data. In this case, x is related to the jerk (a.k.a., jolt) of the device which allows capturing quick motions that may negatively impact the performance of the methods. Using this criterion, a *"still"* segment containing only BCG motion will show significantly smaller motion levels than segments with large and apparent motions such as those of daily activity. To use this value for the analysis, we will define different levels of maximum acceptable motion and only use the segments with values at or below those levels.

IV. Experimental Protocol

Fifteen participants (7 females and 8 males) were recruited to participate in a real-life study in the context of daily life stress measurement. As part of the study, participants were instructed to carry or wear throughout the full workday, for five days of work, the following four devices: head and wrist-worn motion sensors, a smartphone, and a physiological sensor on the chest. During each of the days, participants received on average four prompts on each of the devices to request information about their stress levels. Each of the prompts lasted around 50 seconds with some differences across devices (see more details in [34]). When not answering the questions, participants were not allowed to interact with the devices, but still had to wear or carry them throughout their workday. As the smartwatch device had limited battery life (around 6 hours when running our logging and prompting software), participants were asked to charge the three devices during their lunch break. To ensure that the studied devices were in close proximity to the body, the pieces of data belonging to times when participants were responding to prompts or the devices were charging were excluded from the analysis. The protocol was pre-approved by the Institutional Review Board of the Massachusetts Institute of Technology and participants received compensation of a $200 Amazon gift card upon successful completion of the study.

Thirteen of the participants were graduate students, one was a research assistant, and one was an administrative staff member of a large technical research laboratory. While a large part of the participants' work happened in front of the computer, there were a wide variety of active events throughout the study, including final exams, classes, public presentations, work meetings and important deadlines. The average age of the group was 29 years with a minimum of 18 and a maximum of 42 years. The average weight was 69.39 kilograms with a minimum of 40.82 and 117.93 kilograms, and the average height was 1.7 meters with a minimum of 1.5 and a maximum of 1.92 meters. All the participants described themselves as healthy without known cardiac, respiratory or musculoskeletal problems. However, two of the participants developed respiratory problems throughout the study (coughing) and paused the data collection for a couple of days.

V. Results

This section provides an overview of the findings of the study. We start by reviewing some relevant information from the laboratory studies to help contextualize the rest of the analysis. Then, we systematically evaluate the performance of each of the three wearable BCG methods during real-life. Finally, we quantify the distribution and frequency of *"still"* moments for each of the devices in our study.

A. Laboratory Overview

This work leverages methods developed in laboratory conditions and tests them in a real-life work environment. For each of the laboratory experiments, 12 participants were recruited to hold three body postures (standing up, sitting down and lying down) during two separate minutes (one before, and another after, physical exercise) while capturing motion data from each of the considered locations. Table I summarizes the best results obtained for each of the studies in the context of heart rate estimation. While each of the previous analyses explored different modalities and sensor combinations, the table includes only the best performing combination and the mean absolute error when estimating heart rate. To simplify the analysis, the rest of the results presented here will consider only the best performing combination for each of the locations. That is, we will use the accelerometer for the smartphone, a combination of accelerometer and gyroscope for the wrist-worn device, and the gyroscope sensor for the head-worn device.

Using the motion level defined above, Fig. 2 shows the histogram of motion values derived from accelerometer data observed during each of the laboratory experiments. As can be seen, the distribution of motion levels is very similar for the three devices, but their average and range varied depending on the location. In particular, the average motion levels were 0.0146 (standard deviation = 0.0049), 0.0236 (STD = 0.0077), and 0.0501 (STD = 0.0215) for the pocket, the wrist, and the head locations, respectively. These differences are to be expected as both the wrist and the smartphone are in more peripheral locations, further away from the chest where the motions are more prominent. The following sections mainly focus on the motion ranges of each device to help improve the resolution of the results and better study the impact of different motion levels.

B. Real-Life Heart Rate Estimation

After excluding segments of data when participants were charging the devices and not providing self-reports, there

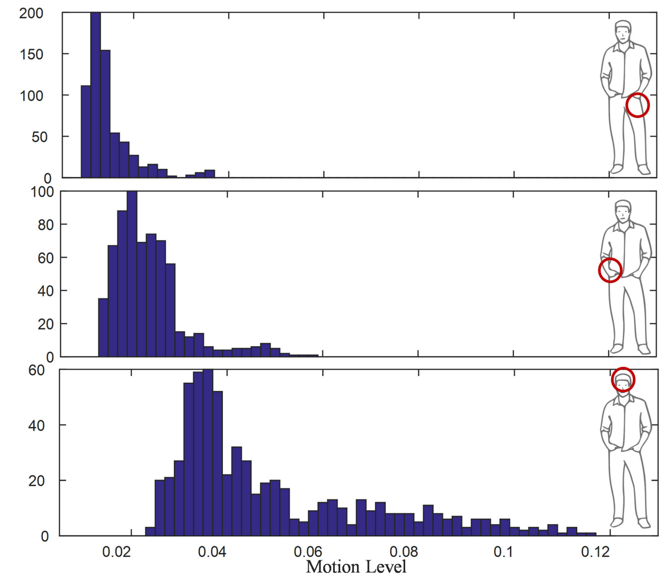

Fig. 2. Distribution of motion levels observed in the laboratory experiments for the pocket (top), wrist (middle), and head (bottom) accelerometer sensors during stationary body positions. N: 648 per histogram.

were around 481, 441 and 435 hours for each of the sensors inside the smartphone, the wrist-worn, and the head-worn wearable devices, respectively. On average, each participant provided around 6 hours (STD = 0.91) of useful recordings per day per sensor, and around 30 hours (STD = 4.7) by the end of the study. The differences across devices were due to several factors such as device batteries running out, forgetting to charge some of the devices, and occasional malfunctioning of some of the devices. After segmenting the data into 20-second pieces, we obtained a total of 920 K segments for each of the two sensor modalities (gyroscopes and accelerometers). From these segments, the FDA-cleared device yielded heart rate estimations with a confidence level above 50% for around 84% of them. Therefore, we consider around 771 K segments for this part of the analysis.

Fig. 3 shows the average mean absolute error (blue lines) and the standard errors (green lines) in beats per minute across the 15 participants (black dotted lines) for different maximum motion levels. In addition, the red-dashed line indicates the motion level threshold for an average absolute error of 5 beats per minute. As can be seen, there is large variability across participants, devices, and motions levels. However, all the curves show a decrease in terms of performance when increasing the motion level, supporting that our motion level estimation effectively captures the negative impact of motion in the studied methods. Among the three devices, the head-worn device is the one that provided the lowest mean absolute errors for the considered motion ranges, followed by the wrist-worn, and then the smartphone. These differences are consistent with the differences observed in the laboratory.

While developed in less challenging settings, the detection methods were still able to yield an average mean error of 5 beats per minute for a certain motion level, which can be further reduced by lowering the motion level thresholds. However, there were some participants for whom the methods did not work as well, even for low motion levels. These individual differences

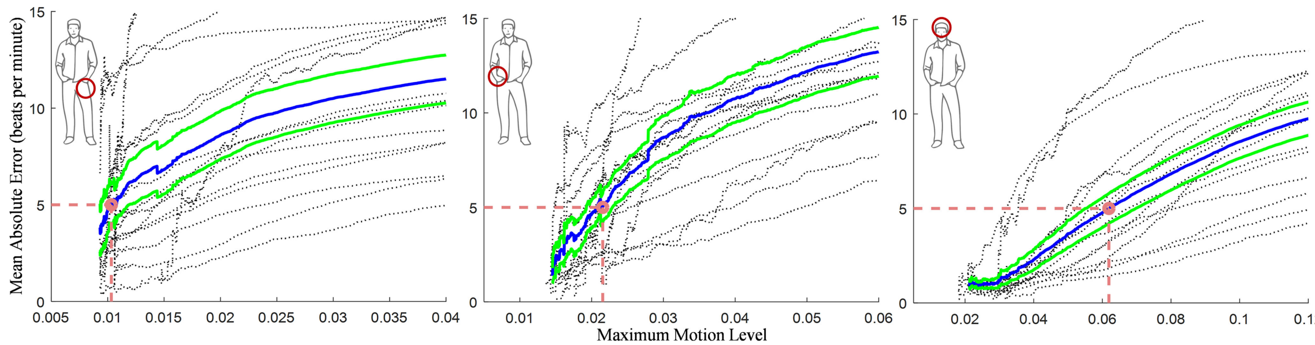

Fig. 3. Relationship between algorithm performance and amount of motion for the pocket (left), wrist (center), and head (right) locations. Each graph shows the average mean absolute error (blue line) and standard error (green lines) across all participants (dotted black lines), as well as the values associated with a 5 beats per minute threshold (red dashed line). As expected, algorithm error deteriorates when increasing the amount of motion. The total number of considered 20-second segments to generate each of the graphs was 282 K, 243 K, and 245 K, respectively.

are positively correlated with the amount of motion each person experienced during their daily activity. Thus, participants who remained sitting at their desk in front of the computers for a majority of the time, yielded the lowest mean absolute errors and participants who were more active during their day usually yielded the worst performance.

C. Distribution of "Still" Moments

The previous section demonstrates that it is possible to opportunistically and accurately estimate the heart rate of people when the amount of motion is relatively small. This section studies the frequency with which such opportunities happened during daily life in our study.

Since the data were segmented into 20-second segments with an overlap of 75%, there is the potential to generate a new heart-rate estimate every 5 seconds. Indeed, each 5-second piece is potentially covered by 5 sliding 20-second segments. To better capture a potentially usable assessment, we assigned each 5-second segment to the smallest motion level associated with one of the data windows. Fig. 4 shows the distribution of potential assessments for different maximum motion levels when considering the 1358 hours of collected data, which includes all the confidence levels of the FDA-cleared device. To better understand the differences across devices, Fig. 4 also shows a red-dashed line indicating the motion levels that yielded an average mean absolute error of 5 beats per minute. The specific maximum motion levels were 0.0103, 0.0215, and 0.0619 for the pocket, wrist and head locations, respectively, which yielded around 5.02% (STD = 3.91), 3.48% (STD = 3.16), and 22.98% (STD = 11.19) of potential assessments for each of the devices.

As can be seen, the availability of *"still"* segments during the day varies across devices and participants, but it is the largest for the most participants when measured via the head-worn device. The wrist location experienced a greater frequency of motion and, therefore, fewer segments of *"still"* data. Finally, the slope of the curve for the pocket location is steeper than the other ones indicating that a significant portion of the segments where it estimated heart rate (around 40%) were within a very small range of motion levels (between 0.01 and 0.028). Among the three sensor locations, the head-worn sensors showed the largest amount of *"still"* samples suitable for estimating heart rate over the different days.

Considering the previous motion levels, Fig. 5 shows the distribution of *"still"* segments for the pocket (left), the wrist (center), and the head (right) locations. Each of the rows indicate data from a different participant and grey rectangles are used to separate the different days. Black dots indicate that at least one isolated 5-second piece qualified for the assessment during that time. Therefore, a more continuous measurement can be provided whenever there is a larger cluster of dots, which indicates a higher distribution of potential assessments (i.e., increased blue area). As expected, these clusters tend to concentrate in moments when lower motion levels are observed. These data represent the varying activity levels observed throughout the day. The average number of opportunistic measurements per day was 236 (STD = 193), 147 (STD = 131), and 978 (STD = 550) when considering the pocket, the wrist and head locations, respectively. However, it is important to note that different devices collected data for different amounts of time. While there is certainly correlation on the occurrence of measurements across devices, there are also moments in which one of the devices outperforms the others. Fig. 6 shows examples of clean and noisy heart rate estimations from two participants. The number of opportunistic measurements for these samples is 931 (top) and 1427 (bottom) with mean absolute errors of 2.87 (STD = 3.38) and 3.77 (STD = 7.09) beats per minute, respectively. As can be seen on the top graph, different body locations can offer complementary information and can effectively capture a wide range of heart rates (from 60 to 90 in this example). However, quick increases of heart rate associated with large motions (e.g., from 11.30 to 12.30) cannot be captured as they quickly overpass the motion level thresholds. The bottom graph shows that the measurements are closely aligned with the gold standard and can capture moderate fluctuations in heart rate. However, this example contains many outliers, especially around the 50 to 70 beats per minute range. This type of outliers is partly to be expected as the methods did not enforce any type of temporal consistency.

VI. Discussion

This work has evaluated the possibility of using low-cost wearable motion sensors at three peripheral body locations (head, wrist and pocket) for workplace heart rate monitoring. Considering data collected from 15 individuals during five

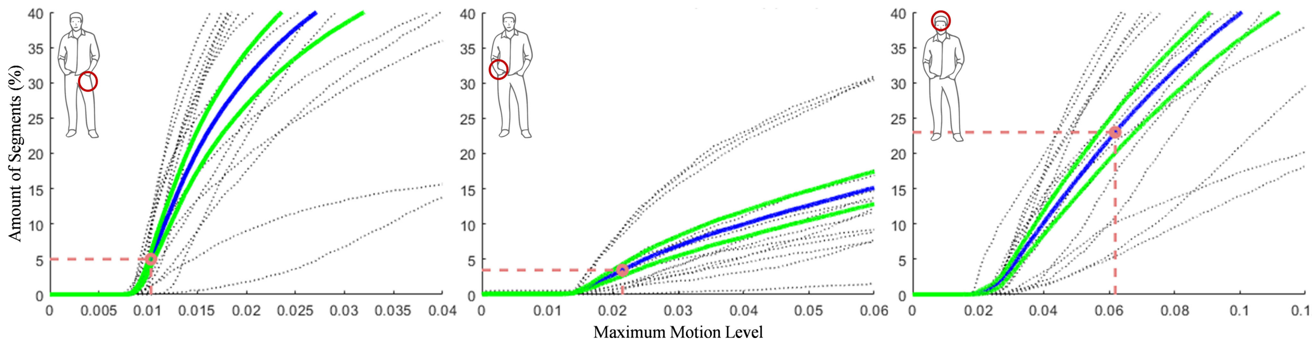

Fig. 4. Percentage of 20-second segments with different amounts of motion level for the pocket (left), wrist (center), and head (right). Each graph shows the average mean absolute error (blue line) and standard error (green lines) across all participants (dotted black lines), as well as the values associated with a 5 beats per minute threshold (red dashed line). As can be seen, the same threshold yields different distributions when considering different devices, with the head location yielding the most useful data (22.98%). The total number of considered hours to generate each of the graphs was 481, 441 and 435, respectively.

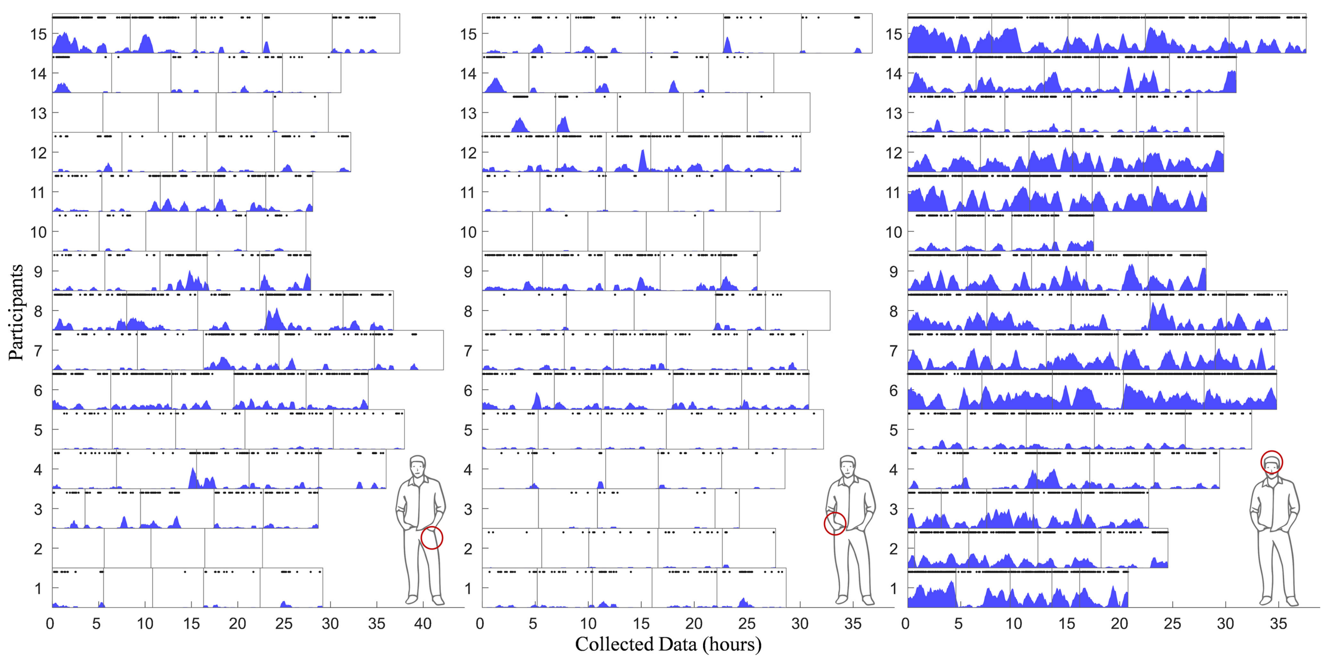

Fig. 5. Temporal distribution of potential assessments from motion sensors in the pocket (left), wrist (center), and head (right) locations, when considering maximum motion levels that yielded error $<=$ 5 beats per minute. Each row represents a different participant, grey rectangles indicate different days, blue areas indicate aggregated distribution, and black dots indicate separate heart rate assessments. The average amount of collected data was around 30 work hours per participant with a daily average of opportunistic heart-rate measurements of around 236, 147, and 978 for the pocket, the wrist and head locations, respectively.

regular workdays per person, we observed that accurate opportunistic heart rate assessments can be obtained from the three locations. However, the head-mounted device yielded significantly more frequent accurate assessments (around 22.98% of the time under 5 beats per minute of error) and, to a lesser extent, the smartphone and the wrist-worn device yielded accurate assessments for around 5.02% and 3.48% of the time, respectively. While these results may suggest that head-worn devices are the most promising location among the three considered, it is important to consider experimental factors.

While the evaluation presented in this work includes naturalistic data of several people during several days, the findings are still dependent on the specific experimental setting. In our case, we considered participants who spent a large portion of their days working in front of computers. This activity may yield better results for head-mounted devices due to the stillness of the head while looking at the computer, and it may also yield worst results for wrist-worn devices due to the constant computer typing. People working in different contexts (e.g., surveillance, transportation) or performing different types of activities (e.g., sleeping) will have different patterns of physical activity. In addition, this study relied on state-of-the-art hardware at the time of the study, but it is important to note that different hardware specifications were used at each of the body locations. While we expect the impact of these differences to be small, a more unbiased comparison would consider identical hardware across body locations. Another relevant factor in our study is that participants received a significant monetary reward. While this compensation allowed us to minimize study drop-outs and increase the quality of the data, it is important to note that

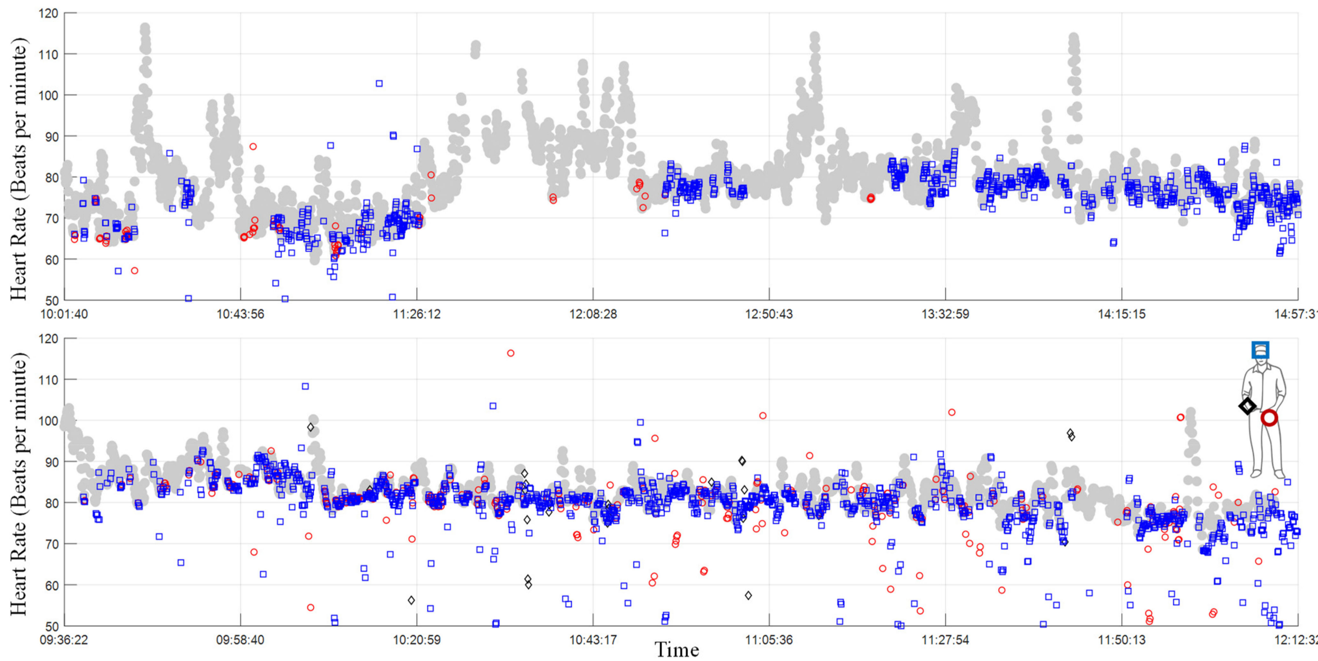

Fig. 6. Clean (top) and noisy (bottom) opportunistic heart rate estimations for two participants using motion sensors in the pocket (red circles), on the wrist (black diamonds), and on the head (blue squares) during *"still"* moments. The gold standard (grey circles) were captured with a chest-worn FDA-cleared ECG device.

real-life participants may not be similarly motivated to carry the devices in the same way as described in this study. For instance, female users may not necessarily carry their smartphone in their trousers [34]. Finally, our study considers healthy individuals without known cardiac, respiratory or musculoskeletal problems which allowed us to partially control unwanted sources of artifact. Future studies, however, will need to consider these populations as they are the ones that can more directly benefit from opportunistic physiological assessments.

To perform the evaluation, we relied on three methods which were previously developed in the context of controlled laboratory scenarios. While the results presented in this study are very promising, they were not as accurate as those observed in the controlled settings. This difference is to be expected when considering the complexity of daily activity and the amount of motion associated with it. While we expect some of these motions could be detected and corrected, other types of motion are subtler and more challenging to correct. For instance, a person working at the computer can artificially simulate motions like the beating of the heart when tapping their feet due to nervousness or when following the beat of background music. In this case, one of the main research challenges will be to correctly detect the few accurate heart rate estimates among the larger sample of noisy estimates. In this work, we have shown that a simple motion level can effectively discriminate between different error levels, but more complex approaches (e.g., [18], [35]) may be used to increase the frequency of opportunistic assessments. As the analysis presented in this work mostly focuses on *"still"* moments during the day, the measurements are more strongly associated with resting heart rate. Future work will need to consider a more in-depth analysis of the measurements at different temporal resolutions (e.g., day, hour) to better assess the potential applications.

Finally, this work has considered wearable motion sensors at three different body locations that offer a good representation of the current landscape of existing wearable solutions but significantly differ in terms of availability. It is estimated that the number of smartphones users worldwide will reach 2.87 billion by 2020 [36]. Even if these devices could only provide one or two opportunistic assessments each day, it could quickly generate a large amount of health data with potentially invaluable medical importance. In addition, different people may be more willing or able to carry different types of devices. Some of the relevant factors include whether users already wear devices with a similar form factor (e.g., glasses, watches), whether they are in social settings where a device may have stigma, and/or whether there is some perceived benefit from carrying the devices [34]. In the future, however, we expect to have more varied form-factors (e.g., jewelry, earrings, T-shirt buttons) that could contain low-cost motion sensors that provide additional benefits for different contexts. Research studying the origin of cardiac signals (e.g., [37], [38]) and how they propagate throughout the body (e.g., [39]–[41]) may provide more insights toward the development of general purpose adaptive methods.

VII. Conclusion

Wearable motion sensors are ubiquitous and offer a unique opportunity to not only track apparent behavioral activity but also provide comfortable opportunistic low-cost physiological assessments of resting heart rate during the day without the expense of a dedicated heart-rate sensor such as a photoplethysmograph. This work examined the ability of three consumer motion-sensing devices, worn in the pocket, on the wrist or on the head, to obtain automated assessments of heart rate in the natural workplace. While there are still many challenges to be addressed, and motion-based estimation is not intended to replace continuous clinical assessments or to be used in medical decision-making, we have shown it is possible to obtain wellness samples of resting heart rate through the use of low-cost and energy-efficient motion sensors, worn in daily life, an advance that could potentially make such assessments more frequent and easily available.

References

[1] G. Tröster, "The agenda of wearable healthcare," *Yearbook Med. Inform.*, vol. 14, no. 1, pp. 125–138, Jan. 2005.

[2] S. Cook, M. Togni, M. C. Schaub, P. Wenaweser, and O. M. Hess, "High heart rate: A cardiovascular risk factor?" *Eur. Heart J.*, vol. 27, no. 20, pp. 2387–2393, Oct. 2006.

[3] Y. L. Zheng *et al.*, "Unobtrusive sensing and wearable devices for health informatics," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1538–54, May 2014.

[4] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," *Physiol. Meas.*, vol. 28, no. 3, pp. R1–R39, 2007.

[5] L. Bao and S. S. Intille, "Activity recognition from user-annotated acceleration data," in *Proc. Int. Conf. Pervasive Comput.*, 2004, pp. 1–17.

[6] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga, "Complex human activity recognition using smartphone and wrist-worn motion sensors," *Sensors*, vol. 16, no. 4, pp. 426–449, Mar. 2016.

[7] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surv. Tut.*, vol. 15, no. 3, pp. 1192–1209, Jul.–Sep. 2013.

[8] A. G. Bonomi, L. M. Eerikäinen, F. Schipper, R. M. Aarts, H. M. De Morree, and L. Dekker, "Detecting episodes of brady-and tachycardia using photo-plethysmography at the wrist in free-living conditions," in *Proc. Comput. Cardiol. Conf.*, 2017, pp. 1–4.

[9] A. G. Bonomi *et al.*, "Atrial fibrillation detection using photo-plethysmography and acceleration data at the wrist," in *Proc. Comput. Cardiol. Conf.*, 2016, pp. 277–280.

[10] J. Hernandez, Y. Li, J. Rehg, and R. W. Picard, "Cardiac and respiratory parameter estimation using head-mounted motion-sensitive sensors," *Eur. Alliance Innov. Endorsed Trans. Pervasive Heal. Technol.*, vol. 15, no. 1, pp. 1–10, 2015.

[11] J. Hernandez, D. McDuff, and R. W. Picard, "BioWatch: Estimation of heart and breathing rates from wrist motions," in *Proc. 9th Int. Conf. Pervasive Comput. Technol. Healthcare*, 2015, vol. 15, no. 3, pp. 169–176.

[12] J. Hernandez, D. McDuff, and R. W. Picard, "BioPhone: Physiology monitoring from peripheral smartphone motions," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2015, pp. 7180–7183.

[13] M. Haescher, D. J. C. Matthies, J. Trimpop, and B. Urban, "A study on measuring heart- and respiration-rate via wrist-worn accelerometer-based seismocardiography (SCG) in comparison to commonly applied technologies," in *Proc. Workshop Sensor-Based Activity Recognit. Interact.*, 2015, pp. 1–6.

[14] R. McConville *et al.*, "Online heart rate prediction using acceleration from a wrist worn wearable," in *Proc. KDD Workshop Mach. Learn. Med. Healthcare*, 2018, pp. 1–4.

[15] J. W. Gordon, "Certain molar movements of the human body produced by the circulation of the blood," *J. Anatomy Physiol.*, vol. 11, no. Pt 3, pp. 533–536, Apr. 1877.

[16] I. Starr, A. J. Rawson, H. A. Schroeder, and N. R. Joseph, "Studies on the estimation of cardiac output in man, and of abnormalities in cardiac function, from the hearts recoil and the bloods impacts: The ballistocardiogram," *Amer. J. Physiol.*, vol. 127, no. 1, pp. 1–28, Oct. 1939.

[17] W. Dock, H. Mandelbaum, and R. A. Mandelbaum, "Ballistocardiography in medical practice," *J. Amer. Med. Assoc.*, vol. 146, no. 14, pp. 1284–8, Aug. 1951.

[18] L. Giovangrandi, O. T. Inan, R. M. Wiard, M. Etemadi, and G. T. A. Kovacs, "Ballistocardiography—A method worth revisiting," in *33rd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2011, pp. 4279–4282.

[19] O. T. Inan, M. Etemadi, R. M. Wiard, L. Giovangrandi, and G. T. A. Kovacs, "Robust ballistocardiogram acquisition for home monitoring," *Physiol. Meas.*, vol. 30, no. 2, pp. 169–185, 2009.

[20] E. Pinheiro, O. Postolache, and P. Girão, "Study on ballistocardiogram acquisition in a moving wheelchair with embedded sensors," *Metrol. Meas. Syst.*, vol. 19, no. 4, pp. 739–750, 2012.

[21] M. Brink, C. H. Müller, and C. Schierz, "Contact-free measurement of heart rate, respiration rate, and body movements during sleep," *Behav. Res. Methods*, vol. 38, no. 3, pp. 511–521, 2006.

[22] M. Migliorini *et al.*, "Automatic sleep staging based on ballistocardiographic signals recorded through bed sensors," in *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2010, pp. 3273–3276.

[23] J. Paalasmaa, M. Waris, H. Toivonen, L. Leppakorpi, and M. Partinen, "Unobtrusive online monitoring of sleep at home," in *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2012, pp. 3784–3788.

[24] M. D. Zink *et al.*, "Unobtrusive nocturnal heartbeat monitoring by a ballistocardiographic sensor in patients with sleep disordered breathing," *Sci. Rep.*, vol. 7, no. 1, Dec. 2017, Art. no. 13175.

[25] A. Dinh, "Heart activity monitoring on smartphone," *Biomed. Eng. Technol.*, vol. 11, pp. 45–49, 2011.

[26] S. Kwon, J. Lee, G. S. Chung, and K. S. Park, "Validation of heart rate extraction through an iPhone accelerometer," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2011, pp. 5260–5263.

[27] D. H. Phan, S. Bonnet, R. Guillemaud, E. Castelli, and N. Y. P. Thi, "Estimation of respiratory waveform and heart rate using an accelerometer," in *Proc. 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2008, pp. 4916–4919.

[28] M. Etemadi and O. T. Inan, "Wearable ballistocardiogram and seismocardiogram systems for health and performance," *J. Appl. Physiol.*, vol. 124, no. 2, pp. 452–461, Feb. 2018.

[29] M. Jafari Tadi *et al.*, "Gyrocardiography: A new non-invasive monitoring method for the assessment of cardiac mechanics and the estimation of hemodynamic variables," *Sci. Rep.*, vol. 7, no. 1, Dec. 2017, Art. no. 6823.

[30] W.-Y. Lin *et al.*, "Identification of location specific feature points in a cardiac cycle using a novel seismocardiogram spectrum system," *IEEE J. Biomed. Heal. Inform.*, vol. 22, no. 2, pp. 442–449, Mar. 2018.

[31] D. D. He, E. S. Winokur, and C. G. Sodini, "An ear-worn continuous ballistocardiogram (BCG) sensor for cardiovascular monitoring," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc*., 2012, pp. 5030–5033.

[32] M. Di Rienzo, P. Meriggi, E. Vaini, P. Castiglioni, and F. Rizzo, "24h seismocardiogram monitoring in ambulant subjects," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2012, pp. 5050–5053.

[33] L. Cadmus-Bertram, R. Gangnon, E. J. Wirkus, K. M. Thraen-Borowski, and J. Gorzelitz-Liebhauser, "The accuracy of heart rate monitoring by some wrist-worn activity trackers," *Ann. Internal Med.*, vol. 166, no. 8, pp. 610–612, Apr. 2017.

[34] J. Hernandez, D. McDuff, C. Infante, P. Maes, K. Quigley, and R. Picard, "Wearable ESM: Differences in the experience sampling method across wearable devices," in *Proc. 18th Int. Conf. Human-Comput. Interact. Mobile Devices Serv.*, 2016, pp. 195–205.

[35] A. Q. Javaid *et al.*, "Quantifying and reducing motion artifacts in wearable seismocardiogram measurements during walking to assess left ventricular health," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 6, pp. 1277–1286, Jun. 2017.

[36] eMarketer, "Number of smartphone users worldwide 2014-2020," 2016. [Online]. Available: https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

[37] C.-S. Kim *et al.*, "Ballistocardiogram: Mechanism and potential for unobtrusive cardiovascular health monitoring," *Sci. Rep.*, vol. 6, no. 1, Nov. 2016, Art. no. 31297.

[38] A. Q. Javaid, H. Ashouri, S. Tridandapani, and O. T. Inan, "Elucidating the hemodynamic origin of ballistocardiographic forces: Toward improved monitoring of cardiovascular health at home," *IEEE J. Transl. Eng. Heal. Med.*, vol. 4, Mar. 2016, Art. no. 1900208.

[39] A. D. Wiens and O. T. Inan, "A novel system identification technique for improved wearable hemodynamics assessment," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 5, pp. 1345–1354, May 2015.

[40] A. Wiens, M. Etemadi, L. Klein, S. Roy, and O. T. Inan, "Wearable ballistocardiography: Preliminary methods for mapping surface vibration measurements to whole body forces," in *Proc. IEEE Eng. Med. Biol. Soc.*, 2014, vol. 2014, pp. 5172–5175.

[41] M. Haescher, D. J. C. Matthies, J. Trimpop, and B. Urban, "SeismoTracker: Upgrade any smart wearable to enable a sensing of heart rate, respiration rate, and microvibrations," in *Proc. Conf. Extended Abstr. Human Factors Comput. Syst*., 2016, pp. 2209–2216.