BioPhone: Physiology Monitoring from Peripheral Smartphone Motions

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Abstract—**The large-scale adoption of smartphones during recent years has created many opportunities to improve health monitoring and care delivery. In this work, we demonstrate that motion sensors available in off-the-shelf smartphones can capture physiological parameters of a person during stationary postures, even while being carried in a bag or a pocket. In particular, we develop methods to extract heart and breathing rates from accelerometer data and compare them with measurements obtained with FDA-cleared sensors. We evaluated their accuracy on 12 people across different still body postures (pre- and post- exercise) and were able to reach mean absolute errors of 1.16 beats per minute (STD: 3) and 0.26 breaths per minute (STD: 0.5) when considering different conditions. Furthermore, we evaluated the same methods during regular phone activities, such as when watching a video or listening to a conversation, yielding increased but still comparable error rates for some conditions.**

I. INTRODUCTION

Physiological monitoring during daily life offers the possibility of capturing information about a person's health and fitness. This information is useful to base medical diagnoses in real-life conditions (vs. white-coat influenced conditions) and to help track chronic health conditions and effects of therapeutic interventions. While great strides have been made to provide comfortable physiological monitoring, traditional methods still require attaching electrodes to the skin and/or interrupt daily activities. Due to such challenges, people do not feel compelled to track their vital signs and show low adherence with existing physiological monitoring approaches. In order to address these problems, more comfortable and less disruptive methods are needed.

In recent work [7][8], we have demonstrated that motion sensors embedded in head-mounted and wrist-worn wearable devices such as Google Glass and Galaxy Gear can capture heart and breathing rates accurately. While the results were very promising, not everybody uses these types of wearable devices as they may be cumbersome and stigmatizing. Motivated by these challenges, this work explores the possibility of using motion sensors of currently available smartphones while being carried in different locations on the body (e.g., trouser pocket, shoulder bag) and when used during regular phone activities (e.g., watching a video, listening to a conversation), as depicted on Fig. 1. In the following, we review relevant research in physiological measurement with smartphones. Then, we describe methods to capture heart rate (HR) and breathing rate (BR) from motion data as well as the experimental design to validate them. Finally, we provide a quantitative comparison of our methods with FDA-cleared sensors and concluding remarks.
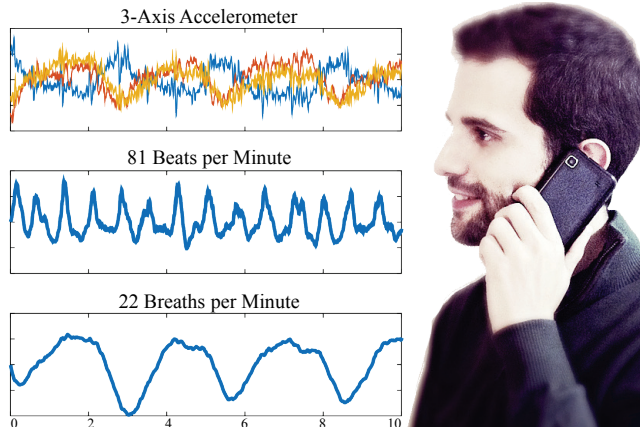

Figure 1. Motion sensors of a smartphones can be used to recover heart and breathing rates of the users during stationary positions and activities such as listening on the phone.

II. MEASURING PHYSIOLOGY WITH SMARTPHONES

Smartphones are now ubiquitous devices and researchers have explored different approaches to leverage their sensors and capture physiological parameters. A commonly explored approach is photoplethysmograpy (PPG). PPG captures the blood volume pulse (BVP) using light reflected from, or transmitted through, the skin [2]. In order to measure PPG, researchers have used the flash and camera of existing smartphones to provide physiological measurements such as HR and BR [11][16]. This approach requires the user to place their finger on the phone in such a way that the flash illuminates the finger while the camera captures color changes. Researchers have also shown that remote cameras and ambient light can also be used to capture the same information [15], freeing users from having to put their fingers on their phone. However, this method still disrupts daily activity as the user needs to position him/her-self in front of the smartphone camera in order for measurements to be made. An alternate measurement technique for capturing cardiovascular parameters is Ballistocardiography (BCG). BCG captures subtle motions of the body due to shifts in mass of blood as the heart pumps [17]. While original research required the person to lie down on a suspended mattress, technological developments have enabled measurement through other devices that are less disruptive (e.g., weighing scale [10], ear-worn device [6]). Researchers have also explored using accelerometers to capture HR and BR by strapping smartphones or sensors onto the chest [5][12][14], where both cardiac and respiratory motions are more prominent. In contrast, this work explores measurement from

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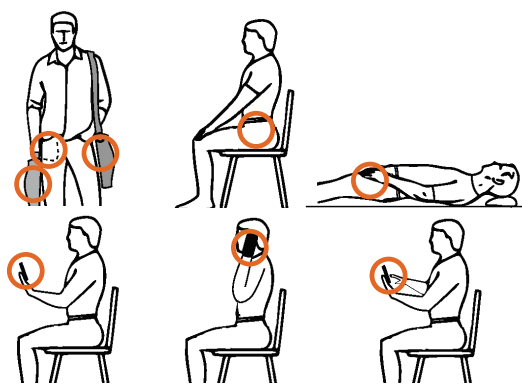
Figure 2. Location of the smartphone during each part of the experimental protocol. Participants remained still while standing up, sitting down, and lying down, which were repeated before and after exercising, followed by watching a video, listening on the phone, and browsing the Internet while sitting down.

natural and comfortable phone locations (e.g., pocket, bag), further from the chest, where physiological motions are more subtle and prone to motion artifacts.

III. METHODS

A. Apparatus

In this work we explore using the 3-axis accelerometer of a Samsung Galaxy S4 to capture physiological parameters from a person carrying their phone. In order to record the data, we wrote Android software that captured data at an average sampling rate of 100 Hz. We then applied the methods proposed below to extract heart and breathing rates. We evaluated the accuracy of our methods against FDA-cleared devices that monitored electrocardiography (ECG) and respiration. In particular, we used a single-lead Alive Technology sensor to capture ECG at a sampling rate of 300 Hz, and the Flex Comp Infinity chest band to capture respiratory motions at a sampling rate of 256 Hz. In order to facilitate the analysis, all signals were synchronized and oversampled to 256 Hz before the analysis.

B. Acclerometer Processing

Given a stream of 3-axis accelerometer data, we developed an automated method for recovering the pulse and respiratory waveforms from which heart and breathing rates can be extracted, respectively. The processing steps are as follows.

Pulse Waveform: A moving average window (n: 15) is subtracted from each of the axes to detrend readings. Then, each of the components is set to have zero mean and unit variance so they have the same relevance and the analysis is more robust to different device orientations. A band-pass Butterworth filter (cut-offs at 7 and 13 Hz, n = 1) is then applied to isolate the BCG motions of each component. The resulting components are then aggregated with a squared root summation of the squared comments. Finally, another band-pass Butterworth filter (0.66 – 2.50 Hz, n = 1) is applied to obtain the final pulse waveform.

Respiratory Waveform: Similarly to the previous processing steps, a moving average window (8.5 seconds) is first subtracted from each of the components which are then z-scored. In order to remove additional noise, we use

Independent Component Analysis (Jade implementation [3]). To isolate the respiratory motions, the resulting components are then band-pass filtered with a Butterworth filter (0.13 Hz – 0.66 Hz, n = 1). Finally, we automatically select the most periodic component as the final respiratory waveform. Periodicity of the signal was estimated by the maximum magnitude achieved in the frequency domain within the previously used frequency range.

These algorithms are motivated by our previous work [7][8][15], which considered different datasets and modalities to extract physiological parameters. The methods were adjusted to be able to correct undesired motion artifacts (e.g., different window sizes) and capture more subtle motions (e.g., lower filter orders).

C. Heart and Breathing Rate Estimation

Once the signals are processed, frequency analysis is performed to extract heart and breathing rates. For heart rate we calculate the Fast Fourier Transform (FFT) of the pulse waveform and find the frequency corresponding to the maximum peak within the range 0.66 Hz and 2.5 Hz, corresponding to 45 and 150 beats per minute, respectively. For breathing rate estimation we calculate the FFT of the respiratory waveform and find the frequency corresponding to the maximum peak within the range 0.13 Hz and 0.66 Hz, corresponding to 8 and 45 breaths per minute, respectively. For the case of HR estimation from ECG signals, we use the Pan and Tompkins method [13] to detect the R peaks, and then compute HR as 60/(average distance between peaks).

D. Experimental Protocol

In order to validate the physiological measurements from the smartphone, we recruited 12 participants (six females) to perform a two-part experiment approved by the Institutional Review Board of the Massachusetts Institute of Technology. For the first part of the experiment, each participant was asked to hold three different body postures (standing, sitting and lying down) for two separate minutes: before and after pedaling on a static bike for a minute. This procedure enabled capture of a large range of physiological parameters as well as studying the impact of different body postures that have been shown to mediate BCG signals [1][7][8]. Throughout this part of the experiment, participants were asked to carry a phone in their pocket. When in the standing position participants were also asked to carry two bags with phones inside; one in the left hand and the other hanging from the right shoulder. This procedure enabled capture of different phone carrying behaviors, which are more common for specific demographics (e.g., females) [4][9]. For the second part of the experiment, participants were asked to perform several traditional phone activities while sitting down. Specifically, participants had to watch a video, listen to a conversation, and browse the Internet for a minute each. During this part of the experiment, participants were instructed to hold the phone as they would during their regular phone activity. Fig. 2 shows an overview of the location of the phone for all the conditions. The duration of the study was around 30 minutes and participants were compensated with a $5 Amazon gift card.

	TABLE I.		HEART RATE ESTIMATION						TABLE II.		BREATHING RATE ESTIMATION					
	Pocket			**Bag**		**Hand**			**Pocket**			**Bag**		**Hand**		
	Sitting	*Supine*	*Stand*	*Hand*	*Shoulder*	*Watch*[+]	*Listen*[+]	*Browse*[+]	*Sitting*	*Supine*	*Stand*	*Hand*	*Shoulder*	*Watch*[+]	*Listen*[+]	*Browse*[+]
ME	1.97	**1.16**	3.37	7.90	**2.38**	**2.37**	3.71	10.09	**0.26**	0.92	2.16	2.26	**2.05**	2.24	**0.33**	1.47
STD	**2.93**	3.00	6.67	11.56	**4.85**	**4.97**	7.40	12.42	**0.50**	2.46	3.41	3.91	**3.40**	3.71	**0.63**	2.58
RMSE	3.53	**3.21**	7.46	13.98	**5.39**	**5.48**	8.25	15.96	**0.56**	2.62	4.03	4.51	**3.96**	4.32	**0.71**	2.95
CC	**0.96**	0.95	0.86	0.65	**0.92**	**0.83**	0.75	0.44	**0.99**	0.83	0.62	0.50	**0.63**	0.58	**0.98**	0.78

ME = Mean absolute error (beats/breaths per minute), STD = Standard deviation of the absolute error, RMSE = Root mean squared error, CC = Pearson's correlation coefficient (p < 0.001 for all correlations). N = 216 for each column except for [+] which N = 108

IV. RESULTS

As in previous work (e.g., [7][8][15]) the collected data was divided into segments of 20 seconds with an overlap of 75% (sliding window with 5 second offsets), yielding a total of 1404 segments of data distributed across different conditions. We then extracted HR and BR from each of the segments separately and compared them to traditional laboratory measurements. Tables I and II show a summary of the results across locations and activities for HR and BR, respectively. Fig. 3 shows representative Bland-Altman plots for some of the conditions.

A. Phone in Pocket During Different Body Postures

The left-most columns of the tables show the performance of our methods when the phone was inside the pocket of the participant. These results include estimations across three different body postures – sitting, supine, and standing. In order to cover a larger range of heart and breathing rates we also collected data before and after exercising. As can be seen, both HR and BR estimations show low mean absolute error rates with some differences across the two measurements and body postures. For HR estimation, the mean absolute error achieved during the supine position was significantly better than during the other two positions (T-test, p<0.005). This finding is aligned with previous research [17], which required participants to lie down to minimize the amount of unexpected motion. On the other hand, while the standing position yielded the worst performance across body postures, it still provided reasonably accurate results. For BR estimation, the mean absolute error rate achieved during the sitting position was significantly better than the other two positions (p<0.001). We believe this is the case due to the proximity of the phone to the stomach, which is more directly influenced by respiratory motions. Overall, BR estimations were more accurate than HR estimations due to their larger amplitude and lower frequency range. The motions were more easily transferred through the body and sensed by peripheral accelerometers in the phone.

B. Standing: Pocket vs Hand-bag vs Shoulder-bag

While the participants were holding the standing position, three different phones at separate locations were simultaneously monitoring motion data: one inside the pocket, another inside a bag in the left hand, and another inside a bag hanging from the right shoulder. When comparing results across locations, the phone inside the bag hanging from the shoulder yielded slightly better mean absolute error for BR and significantly better for HR
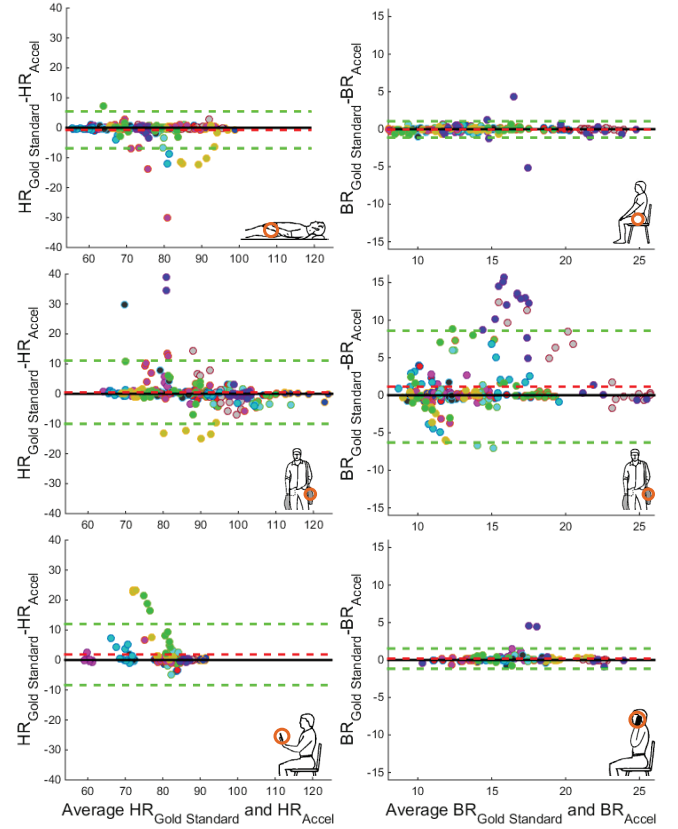

Figure 3. Bland-Altman plots for heart (left) and breathing rates (right) of the conditions that yielded the best mean absolute error when the phone was inside the pocket (top), inside the bag (middle), and on the hand (bottom). Mean error is depicted with slashed red and 95% limits are depicted with slashed green lines. (HR: Heart Rate in beats per minute, BR: Breathing Rate in breaths per minute, Accel: Accelerometer). N = 216 for top and middle graphs, and N = 108 for bottom graphs.

estimation (p<0.001). We believe this result is due to a combination of several factors. When hanging a bag from the shoulder, the accelerometers can capture more accurate ballistocardiographic and respiratory motions that are more prominent along the vertical axis [17] and around the chest location. Moreover, when hanging a bag from the shoulder the amount of contact with the body is large and its range of movements are more constrained than when holding the bag from the hand. Overall, these factors can enable easier propagation of the subtle cardiorespiratory motions. During the standing position, one of the participants had difficulties to remain relatively still which negatively impaired some of the results. The data points associated with this participant correspond to the purple dots of the middle graphs of Fig. 3.

C. Phone Activities

While the phone may remain most of the time in one of the locations already considered [4][9], the main purpose of the device is to facilitate performing activities such as communicating with other people. In this section, we provide preliminary analysis of HR and BR estimation while the phone is being used during three, relatively stationary, common activities: watching a video, listening to a conversation, and browsing the Internet.

In terms of HR estimation, both watching and listening yielded slightly worse but still comparable results to the ones obtained when the phone was inside the pocket. However, the mean absolute error was significantly worse when browsing information than the other two activities ($p < 0.001$). Among all the different conditions, this is the only one in which the user is actively manipulating the device and, therefore, is affecting the accelerometer readings more directly. Indeed, subtle touch interactions such as zoom-in, zoom-out and finger taps elicit very similar acceleration patterns to the ones associated with ballistocardiographic beats and could potentially confuse the algorithms. While more complex approaches could be used to detect and cancel the effects of these non-cardiorespiratory motions, larger motions such as the ones observed during daily activities (e.g., walking) could easily preclude the subtle motions associated with the heart beats. In terms of BR estimation, listening to a conversation with the phone next to the ear yielded significantly better results than the other two activities ($p < 0.001$) which was comparable to the results obtained when the phone was inside the pocket during the sitting down position. Interestingly, the performance during the browsing activity was still very accurate, indicating that touch interactions were not confused with respiratory motions probably due to the lower frequency range of the latter.

V. CONCLUSIONS

The previous section demonstrates that physiological parameters such as heart and breathing rates can be recovered from a smartphone via accelerometer measurements while the person is carrying it in different locations or using it during different activities. However, most of the considered conditions involved positions and activities without too much motion (e.g., lying down, watching a video). As shown in the browsing condition, for example, motions such as those presented when interacting with the phone can negatively impair the performance of the proposed methods. Therefore, our methods would only be applicable to provide sporadic assessments during the day when the amount of motion is small (e.g., reading a book, watching TV). Future efforts will focus on extending this research and assess the accuracy and utility of the proposed methods in real-life scenarios.

The results of this work are very encouraging but also worrisome. While currently limited to stationary conditions, this work demonstrates that personal information such as physiological parameters can be captured with existing smartphones offering the possibility for intrusion of privacy. For instance, an application could be used to covertly monitor the physiological responses of individuals to personalize advertisements. While this may be a potential application in the future, it is important to appropriately inform users about how the data is being used. Currently, most smartphone users are not aware that cardiovascular health information can be conveyed simply by carrying or holding a smartphone that contains accelerometers. Findings like the ones presented in this work urge us to reconsider how this type of data is monitored, stored and transmitted to enforce transparency and protect user's privacy of their health-related data.

In summary, this work demonstrates that it is possible to capture physiological parameters from subtle peripheral smartphone motions during stationary positions and activities. While the results are very promising there are still several research challenges that need to be addressed in order to provide continuous physiological measurement. As these methods continue to advance, we hope they will be used to create passive and comfortable assessments that foster greater health and wellbeing during daily life.

REFERENCES

[1] J. Alametsa, J. Viik, J. Alakare, A. Varri, and A. Palomaki. "Ballistocardiography in sitting and horizontal positions," *Physiological Measurement*, vol. 29, no. 9, pp. 1071-1087, 2008.

[2] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," *Physiological Measurement*, vol. 28, no. 3, pp. R1–39, 2007.

[3] J. F. Cardoso, "High-order contrasts for independent component analysis," *Neural Computation*, vol. 11, no. 1, pp. 157–192, 1999.

[4] Y. Cui, J. Chipchase, and F. Ichikawa. "A cross culture study on phone carrying and physical personalization," In *Proc. of Int. Conf. on Usability and Interanationalization*, 2007, pp 483-492.

[5] A. Dinh, "Heart activity monitoring on smartphone," In *Proc. of Int. Conf. on Biomedical Eng. and Technology*, vol. 11, pp. 45-49, 2011.

[6] D. D. He, E. S. Winokur, and C. G. Sodini, "An ear-worn continuous ballistocardiogram sensor for cardiovascular monitoring," In *Proc. of Eng. in Medicine and Biology Society*, pp.5030–5033, Jan. 2012.

[7] J. Hernandez, D. McDuff, and R. W. Picard. "BioWatch: Estimation of heart and breathing rates from wrist motions," In *Proceedings of Pervasive Health*, 2015.

[8] J. Hernandez, Y. Li, J. Rehg, R. W. Picard. "BioGlass: Physiological parameter estimation using a head-mounted wearable device," In *Proc. of Wireless Mobile Communication and Healthcare*, 2014, pp. 55-58.

[9] F. Ichikawa, J. Chipchase, R. Grignani. "Where's the phone? A study of mobile phone location in public spaces," In *Proc. of Int. Conf. on Mobile Technology, Applications and Systems*, pp. 1-8, 2005.

[10] O. T. Inan, M. Etermadi, R. M. Wiard, L. Giovangrandi, and G. T. Kovacs, "Robust ballistocardiogram acquisition for home monitoring," *Physiological Measurement*, vol. 30, no. 2, pp. 169-85, 2009.

[11] E. Jonathan, M. Leahy. "Cellular phone-based photoplethysmographic imaging," *Biophotonics*, vol. 4, no. 5, pp. 293–6, 2011.

[12] S. Kwon, J. Lee, G. S. Chung, and K. S. Park, "Validation of heart rate extraction through an iPhone accelerometer," In *Proceedings of Engineering in Medicine and Biology Society*, pp. 5260–5263, 2011.

[13] J. Pan, and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 32, no. 3, pp. 230-236, 1985.

[14] D. H. Phan, S. Bonnet, R. Guillemaud, E. Castelli, and N. Thi, "Estimation of respiratory waveform and heart rate using an accelerometer," In *Proceedings of Engineering in Medicine and Biology Society*, pp. 4916-4919, 2008.

[15] M. Poh, D. J. McDuff, and R. W. Picard, "Non-contact, automated cardiac pulse measurements using video imaging and blind source separation," *Optics Express*, vol. 18, no. 10, pp. 10762–74, May 2010.

[16] C. G. Scully, J. Lee, J. Meyer, A. M. Gorbach, et al. "Physiological parameter monitoring from optical recordings with a mobile phone," *IEEE Trans Biomedical Enginerring*, vol. 59, no. 2, pp. 303–6, 2012.

[17] 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," *American J. of Physiology*, vol. 127, no. 1, 1939.