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Cardiac and Respiratory Parameter Estimation Using Head-mounted Motion-sensitive Sensors

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Abstract

This work explores the feasibility of using motion-sensitive sensors embedded in Google Glass, a head-mounted wearable device, to robustly measure physiological signals of the wearer. In particular, we develop new methods to use Glass's accelerometer, gyroscope, and camera to extract pulse and respiratory waves of 12 participants during a controlled experiment. We show it is possible to achieve a mean absolute error of 0.82 beats per minute (STD: 1.98) for heart rate and 0.6 breaths per minute (STD: 1.19) for respiration rate when considering different observation windows and combinations of sensors. Moreover, we show that a head-mounted gyroscope sensor shows improved performance versus more commonly explored sensors such as accelerometers and demonstrate that a head-mounted camera is a novel and promising method to capture the physiological responses of the wearer. These findings included testing across sitting, supine, and standing postures before and after physical exercise.

Keywords: Ballistocardiography (BCG), blood volume pulse (BVP), heart rate, respiration rate, head-mounted wearable device, gyroscope, accelerometer, camera, daily life monitoring.

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1. Introduction

Being able to comfortably monitor physiological information during daily life can reduce the costs associated with health measurement and care delivery [37]. For instance, physiological measures such as cardiovascular and respiratory activity can be used for early detection and diagnosis of relevant risk factors of cardiovascular disease [6] as well as for helping to monitor chronic conditions and therapeutic interventions.

Traditional approaches to measure parameters such as heart rate require attaching electrodes to the skin, which is cumbersome for daily life monitoring. However, recent advances in technologies have enabled the creation of wearable devices of reduced sized, weight and power consumption. These devices are in close contact with the body and offer a new set of low-cost unobtrusive sensors that can run continuously during daily activities.

In this work we focus on the motion-sensitive capabilities within a commercial product, the Google Glass (see Fig. 1). Google Glass is a wireless head-mounted device equipped with a touch pad, a see-through display, and most of the sensors available in smartphones. Although the device was not designed for physiological measurement, its unique location on the head of the person provides an opportunity to unobtrusively monitor physiological information during daily activities. In particular, we develop new methods allowing the gyroscope, the accelerometer and the camera embedded in Glass to be used to capture subtle head motions of the wearer that are associated with the mechanical activity of the heart and the respiration of the wearer.

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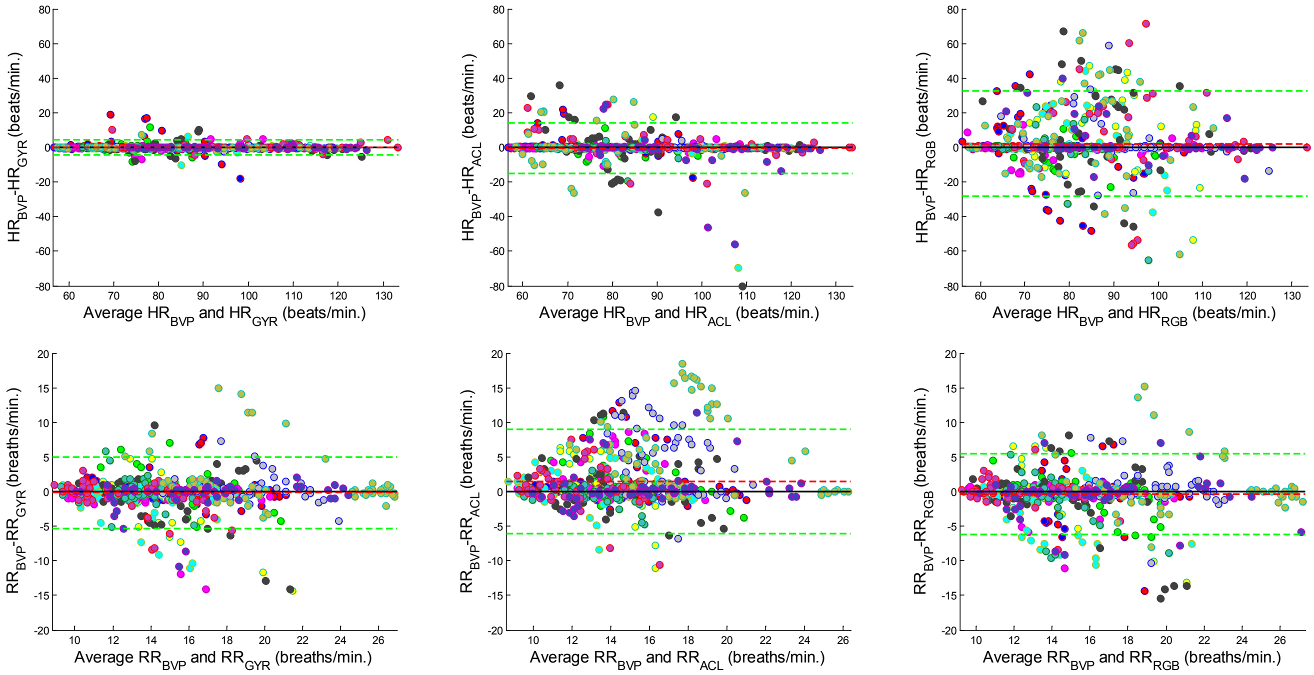

Figure 4. Bland-Altman plots for heart (top) and respiration rates (bottom) using gyroscope (left), accelerometer (center), and camera (right). Each graph shows the agreement of 648 pairs of measurements. Data from different participants are represented with dots of different colors. Mean error is depicted with slashed red and 95% limits are depicted with slashed green lines. (HR: Heart Rate, RR: Respiration Rate, GYR: Gyroscope, ACL: Accelerometer, RGB: Camera)

Table 1. Heart Rate Estimation

Sensor	ME	STD	RMSE	CC
Gyroscope	0.82	1.98	2.14	0.99
Accelerometer	2.51	7.03	7.46	0.91
Camera	7.92	13.4	15.56	0.58
All	1.19	3.42	3.62	0.98

Table 2. Respiration Rate Estimation

Sensor	ME	STD	RMSE	CC
Gyroscope	1.39	2.27	2.66	0.75
Accelerometer	2.29	3.43	4.12	0.41
Camera	1.55	2.59	3.02	0.69
All	1.16	2.04	2.35	0.79

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

Table 3. Mean Absolute Error of Heart Rate

Sensor	Sitting	Standing	Supine
Gyroscope	1.18	0.85	0.44
Accelerometer	3.30	2.18	2.06
Camera	4.51	10.17	9.10
All	1.48	1.17	0.92

Table 4. Mean Absolute Error of Respiration Rate

Sensor	Sitting	Standing	Supine
Gyroscope	1.13	1.97	1.06
Accelerometer	1.87	3.17	1.82
Camera	1.32	1.89	1.45
All	0.94	1.77	0.77

three body postures: sitting, standing, and supine. Tables 3 and 4 show the mean absolute error (beats and breaths per minute, respectively) for each of the different positions and sensors. When estimating heart rate, the most challenging position was sitting down, which is in accordance with the results described in [11]. The results obtained with the gyroscope in this study outperform the results of He et al. [11] for the sitting (ME: 1.27) and supine (ME: 0.84) conditions but not for the standing (ME: 0.72) position. However, the range of heart rates they observed in their study was considerably smaller (55 to 95 beats per minute) in comparison to the ones we elicited (56 to 133 beats per minute). The different results for the camera sensor may be due to a combination of several factors such as the influence of body posture, the accuracy of motion estimation as well as the relative pose of the camera with

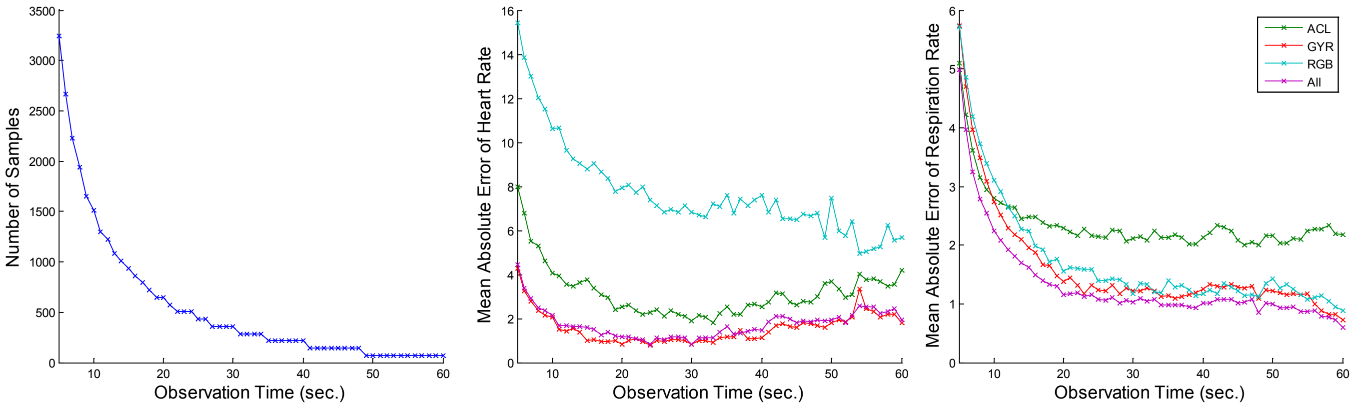

Figure 5. Mean absolute error for heart (beats per minute) and respiration rates (breaths per minute) when considering different window sizes. (ACL: Accelerometer, GYR: Gyroscope, RGB: Camera)

respect to the wearer's head. When estimating respiration rate, the most challenging position was standing up for all the modalities. Apparently, respiratory movements have less influence on head motion while standing. Overall, even the most challenging posture positions yielded low error for the best-performing modality.

6.3. Combination of Modalities

Differences in performance across modalities are partly due to the different types of information being captured by each of the sensors. For instance, while the accelerometer data captures linear accelerations, the gyroscope captures rotations of the device. Furthermore, while some of the sensors may be affected by sampling rate artifacts (e.g., accelerometer and gyroscope), other sensors may provide more constant sampling rates but less accurate information (e.g., camera). Therefore, a combination of different modalities may help to provide more reliable estimates at the cost of computational complexity. To explore this idea, we extracted the heart/respiration rates of each modality separately and computed the median as the final estimate. The bottom rows of Tables 1 and 2 show the results using this late fusion technique. While the heart rate estimation using the gyroscope was still better than the one obtained combining all the modalities, the respiration rate estimation with all three modalities yielded better results than with any of the other modalities alone (reducing the ME to 1.16 breaths per minute, STD 2.04). Although not explored in this work, we expect larger improvements by combining physiological signals in less controlled settings where different modalities might provide complementary information about motion.

6.4. Observation Windows

While combining several sensors may partially address the problem of motion artifacts, an underlying assumption of the proposed methods and evaluation is that the person is holding a motion-less position for the majority of a certain observation window (20 seconds for the previous results). However, being able to remain still for large periods of times during daily life may not be always possible and shorter and more available observation windows may be preferred. In order to explore the performance of our methods for different lengths of observation windows, we split the collected data into segments of different durations following the same criteria described above and assessed their performance. Fig. 5 shows the number of samples obtained for each of the observation windows (left), and the absolute mean error of the different approaches to estimate heart rate (center) and respiration rate (right). As can be seen, heart rate can be computed with a ME of 4 beats per minute with an observation window of only 5 seconds from gyroscope. This error goes below 2 beats per minute for observation windows equal or larger than 10 seconds, reaching its minimum at 25 seconds. The decrease of performance with smaller windows is expected due to several factors. When computing heart and respiration rates, especially in the frequency domain, longer observation windows are preferred to provide more accurate estimates. Moreover, different body locations reflect physiological changes at different times which can negatively bias our estimates.

Although we expected ME would always decrease with longer observation windows, there was a subtle rebound effect for windows above 30 seconds for the accelerometer and gyroscope data. Visual inspection suggested that this rebound was due to missing beats due to the non-uniform sampling rates of these two sensors, which became more significant when reducing the amount of samples. This effect was not observed when estimating respiration rate, where larger observation windows always improved performance. This finding is in accordance with the previous observation as breathing rate operates in a lower frequency range and the non-uniform sampling rate did not negatively affect the signal. Using the longest observation window (60 seconds) and a combination of all the sensors, the ME was reduced to 0.6 breaths per minute (STD: 1.19).

Note that the fusion of the three modalities performs more or less the same as the best modality when estimating the heart rate, and consistently leads to slightly better results than the individual modalities when estimating respiration rate. These results are promising for real-life monitoring where the head of the person is more likely to remain still for shorter periods of time than longer ones. In practice, the duration of the observation window and the accuracy is a trade-off that needs to be carefully chosen when deciding on a specific population and/or application. For instance, children may have more problems to remain still than adults and shorter and less accurate windows may be preferred. However, longer and more accurate readings may be more accessible and adequate in certain scenarios such as sleeping or practicing meditation.

7. Discussion

The previous sections have shown that it is possible to capture physiological parameters from acceleration, gyroscope and camera. The results from different modalities are consistent and the mean absolute errors are small, which further justify our methods. Furthermore, some of our results were improved by combining several modalities and changing the observation windows. While we expect the combination of sensors will yield improved assessments of physiological parameters during daily life, there are critical differences among sensors that need to be considered.

Both accelerometer and gyroscope require considerably less energy than the camera and, therefore, allow for longer periods of monitoring without charging the batteries. With the current version of device, we were able to continuously record gyroscope and accelerometer data for around 8 hours with an average sampling rate of 50 Hz. These two sensors directly capture complementary aspects of the wearer's head motion. For instance, while driving a car, the accelerometer readings may be influenced by external forces such as changes of speed; however, the gyroscope will provide cleaner signals associated with the rotation of the head of the driver. In this specific case, the accelerometer and the gyroscope can provide meaningful information about both the context and the physiology.

The camera requires significantly more energy (the current battery lasts approximately 20 minutes of continuous monitoring), but also provides some critical benefits. The location of the camera of the head-mounted device in this work is located above the right eye (see Fig. 1). This setup offers the opportunity of capturing the environment from the wearer's perspective. This information is useful not only to extract physiological parameters as demonstrated in this work, but also to capture rich contextual information that helps infer the sources of physiological responses. For instance, a person exercising at the gym and a person giving a public presentation may show similar increases in heart and respiration rates. However, the same arousal of physiological signals is due to different reasons (physical stress vs. affective-cognitive stress). The visual context in these cases, therefore, plays a critical role to interpret the physiological signals. Furthermore, linking physiological information with visual imagery can be useful in a wide variety of applications such as catalyzing introspection [15], augmenting human memory [17], and improving social communication [23].

One of the main challenges when estimating physiological parameters from motion in real-life scenarios is the presence of large ego-motion due to physical activity. Daily activities such as walking or speaking with other people involve large body movements that might occlude the subtle heart and respiratory motions. Although this study did not directly address this issue, we evaluate our methods for a large range of observation windows. For instance, with only a 5-second observation we were able to provide estimates of heart rate with a ME of 4 beats per minute with gyroscope. This observation window is significantly smaller than windows reported on similar studies (e.g., >70 sec. in [2], >20 sec. in [11], 30 sec. in [30]). An important area of research is to understand how often these observation windows are accessible during daily life activity. In a relevant study, Rienzo et al. [33] monitored sternal seismocardiogram of 5 participants during 24 hours and found that there were more than 100 5-second segments per hour with good quality acceleration data during the day and three times higher during the night. These numbers were quickly reduced with longer observation windows. These results are promising for non-intrusive physiological assessments. However, the location and types of sensors of this study are different, and can have an impact on the statistics. Future research will assess the availability of good quality data from participants wearing a head-mounted device during daily life activity.

8. Conclusions

In this work we have explored the possibility of using different motion-sensitive sensors of a head-mounted wearable device to extract physiological parameters of the wearer. In particular, this work has 1) proposed real-time algorithms to process head-mounted motion-sensitive sensors, 2) provided validation of heart and respiration rate estimation with FDA-cleared sensors in a controlled laboratory setting, and 3) quantitatively compared sensor modalities, body postures, and observation windows.

Among the three motion-sensitive sensors we considered, we have shown that the gyroscope outperformed the other sensors, including the accelerometer upon which prior BCG measurements are mostly based (e.g., [7][11][20][29][33]). We believe this improvement is partly due to the above-eye location of the sensor and its capability to capture amplified rotational movements of BCG. Moreover, we have demonstrated that analyzing the ego-centric view of head-mounted camera is a novel and promising method to harvest physiological information of the wearer, with the benefit of also providing insightful visual context. Finally, as each of the modalities captures different aspects of motion, their combination offers the opportunity to improve overall performance. For instance, this work has demonstrated preliminary improvements in the estimation of respiration rates when combining the estimations of the three modalities.

Future efforts will consider evaluating other modalities and developing novel methods to combine them depending on contextual information such as body postures or activities. We have also started to work on more sophisticated methods that can handle large motions associated with daily activities, which is fundamental to apply the proposed methods in real world settings. In the future, we will also be analyzing other relevant physiological parameters such as heart rate variability (e.g., [4]) as it has been shown to be associated with cognitive load [26] and stress [16][25]. The key to this parameter is to obtain highly accurate timing of the heartbeats and, therefore, uniform sampling rates and filters without phase delays will be explored.

In summary, this work has shown a new capability to provide accurate real-time heart-rate and respiration measures from motion-sensitive sensors available in today's head-mounted wearable Google Glass. With the continuous technological improvements and commercial reach of new devices, we expect our results will help facilitate non-intrusive access of meaningful physiological information during daily activity. We are looking towards a future where this type of information is more accessible and is used to enhance the delivery of primary health care and the monitoring of chronic conditions.

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