BioInsights: Extracting Personal Data from "Still" Wearable Motion Sensors

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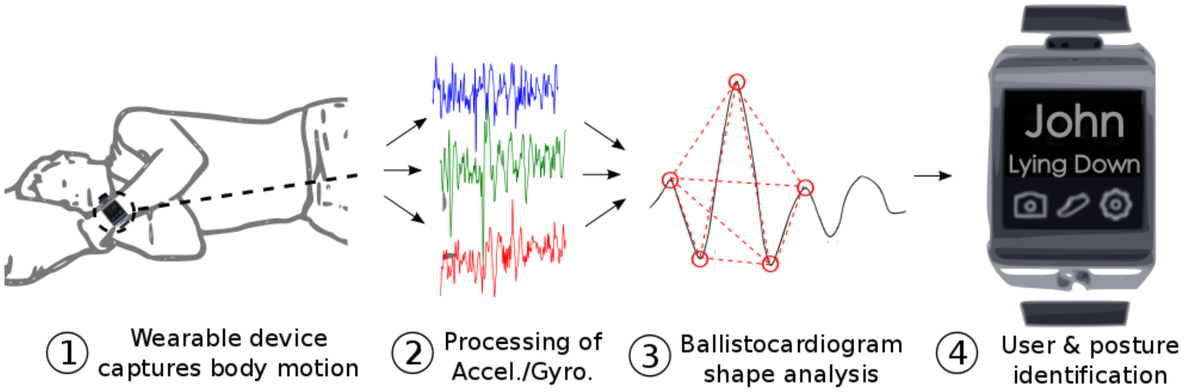

Fig 1. Overview of the proposed identity and posture recognition: 1) wearable devices (Galaxy Gear or Google Glass) capture accelerometer and gyroscope measurements, 2) signals are then processed to extract ballistocardiographic (BCG) information, 3) shape-based features are extracted from the average BCG waveform, and 4) person and posture classification are performed.

***Abstract*— During recent years a large variety of wearable devices have become commercially available. As these devices are in close contact with the body, they have the potential to capture sensitive and unexpected personal data even when the wearer is not moving. This work demonstrates that wearable motion sensors such as accelerometers and gyroscopes embedded in head-mounted and wrist-worn wearable devices can be used to identify the wearer (among 12 participants) and his/her body posture (among 3 positions) from only 10 seconds of "still" motion data. Instead of focusing on large and apparent motions such as steps or gait, the proposed methods amplify and analyze very subtle body motions associated with the beating of the heart. Our findings have the potential to increase the value of pervasive wearable motion sensors but also raise important privacy concerns that need to be considered.**

Keywords*— *accelerometer; gyroscope; smartwatch; wrist; head; ballistocardiography; person identification; posture recognition; Support Vector Machines.

I. INTRODUCTION

Continuous developments of technology such as electronic miniaturization and increased battery life have enabled the creation and adoption of a wide range of wearable devices. These devices come in many different forms such as head-worn (e.g., Google Glass, Oculus Rift) or wrist-worn (e.g., Galaxy Gear, Apple Watch) devices, and include a large variety of sensors (e.g., microphone, camera). Among all the different sensors, accelerometers are probably the most pervasive ones due to their low cost and large number of applications. For instance, commercially available activity trackers (e.g., Basis Peak, Fitbit Charge) mainly rely on accelerometers to count the number of steps, and physiological monitoring devices (e.g., Empatica E4, Zephyr BioHarness) include motion sensors to capture not only activity but also sources of signal artifacts. While most applications of accelerometers focus on the analysis of large motions associated with daily activity (e.g., steps, change of body posture), the work we present here focuses on very subtle body motions that are mainly detectable when remaining relatively "still." Recently published work [7] has demonstrated that motion sensors embedded in a head-mounted wearable device can capture the subtle motions associated with the beating of the heart and respiration, even when the sensors are located far from the torso. In this work we explore how analyzing these cardiac motions can provide additional information about the person. In particular, we explore whether and how accurately accelerometers and gyroscopes from two types of wearable devices (head-worn and wrist-worn) can be used to identify a user (among 12 participants) and his/her body posture (among 3 positions). Furthermore, we discuss how our findings may solve some of the current challenges of wearables as well as how they pose new potential challenges to privacy.

This work is organized as follows. First, we provide an overview of relevant literature on recognition of cardiac motions and person identity/body position. Then, we describe the experimental setting, and follow with a description of the novel methods and evaluation. Finally, we discuss the results and implications of this new work as well as highlight potential directions for future research.

II. Background Research

Every time our heart beats, the movement of the blood shifts the center of our body mass, eliciting subtle and repetitive body motions. This signal, also known as ballistocardiography (BCG), was popularized by Starr et al. [12] who used a suspended supporting structure to magnify and study the BCG motions of people while lying down. With the continuous improvements of technology, researchers have studied less constrained settings and successfully measured BCG from daily objects we are frequently in physical contact with (e.g., modified chair [6], bed mattress [9]) and, more recently, from wearable devices (e.g., smartphones on the chest [3] and a head-mounted wearable device [7]). BCG signals as well as other physiological signatures have been shown to be influenced by several factors such as posture and gender [1] and, therefore, offer the opportunity to indirectly provide access to personal information. This work extends these previous findings by showing how this information can be used to identify the wearer and recognize 3 of his/her body postures.

In the context of person identification, two separate studies [6][13] have explored using a pressure-sensor on a chair and an accelerometer attached to the chest, respectively, to identify people while sitting down. In the context of body posture recognition, only one study [9] explored using a custom-made mattress that measured BCG from the chest and the leg of people to discriminate several positions while lying down (supine, left, prone and right). While these studies demonstrated the possibility of performing person and posture recognition from motion signals, their methodologies present some important limitations that can be improved upon. For instance, two of the works [6][13] only considered one body posture, limiting the well-known variance that is associated with different positions [1]. Furthermore, their approaches also required the simultaneous measurement of electrocardiography (ECG) for the purpose of beat segmentation. In another case [9], researchers used data of the same person for training and testing, limiting the possibility of using their methods with different people.

Our work makes several new contributions. First, we consider three different body postures before and after exercise, which provides important real-world variation to the BCG data. Second, the body posture recognition analysis in this work tests with data of only new people (no one in the training set was also in the test set). This test offers a more realistic and challenging scenario. Third, we evaluate for the first time the use of gyroscopes to perform person and posture recognition from motion data. Finally, our work depends on wearable motion sensors alone, without requiring additional sticky electrodes or ECG measurements. Our sensors are worn on comfortable peripheral locations (head and wrist) instead of traditional locations (torso) where heart beat motions are more prominent and clean. Being able to access such information from peripheral wearables offers the opportunity to provide more frequent and comfortable measurements during daily life.

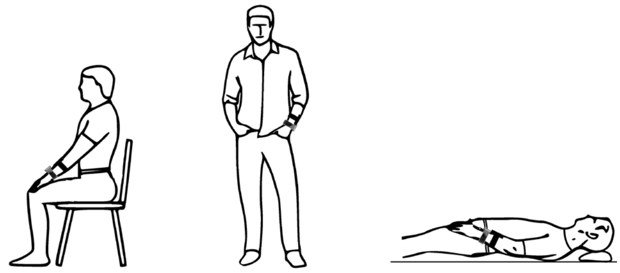

Fig. 2. Participants held three different positions (sit down, stand up, lie down) before and after exercise, while wearing Google Glass or Samsung Galaxy Gear.

III. Data Collection

Two sets of 12 participants (balanced gender) with ages ranging from 22 to 34, and no known cardiac or respiratory abnormalities, were asked to wear either a Google Glass or a Samsung Galaxy Gear during a 25 minute experiment in exchange for a $5 Amazon gift card. After signing a written consent form, participants were requested to hold three different body postures (sitting down, standing up and lying down), as show in Fig. 2, during two one-minute periods: one before and another after performing physical exercise. This allowed us to collect data for a number of body postures and physiological ranges, which are known to change the shapes of the signals. For the exercise activity the participants pedaled for one-minute on a stationary bike. This experimental protocol was approved by the Institutional Review Board of the Massachusetts Institute of Technology.

In order to collect the data, we developed a custom Android software application, which enabled us to simultaneously record the 3-axis accelerometer and the 3-axis gyroscope readings from both devices. While the accelerometer captures linear accelerations (meters/second^2), the gyroscope captures the rate of rotation (radians/second) of the device. Both types of motions have been shown to be complementary when capturing cardiac information from motion [7]. The average sampling rates were 50 Hz and 100 Hz for the Glass and Gear, which were the maximum stable values that could be achieved by the devices at the time of the data collection. However, the streams of data were interpolated to a constant sampling rate of 256 Hz as performed in [7].

IV. Methods

The experiment resulted in six separate one-minute recordings per individual. In order to create several sample readings for each of the conditions, we split the data into non-overlapping segments of 10 seconds each (similar to [6]) yielding 432 segments equally balanced in terms of person and body posture. For each of these segments we applied several processing steps to amplify BCG motions and to extract representative features that could be used for the analysis. Each sensor modality (accelerometer and gyroscope) was processed separately.

A. Recovering the BCG Waveform

In order to isolate the subtle motions associated with the heartbeats, we performed the following steps. First, each of the 10-second sensor components (e.g., each of the 3 axis of the accelerometer) was normalized to have zero mean and unit variance. Next, we subtracted an averaging filter (window of 35 samples) to detrend the data and to remove relatively slow motions such as respiration and stabilizing body motions. Finally, a Butterworth band-pass filter (cut-off frequencies of 4-11 Hz) was used to recover the BCG waveform from each component. As not all the components carry relevant cardiac information, we automatically selected the most periodic component of each sensor modality (accelerometer and gyroscope) by choosing the signal with highest amplitude response in the frequency domain. All the steps and parameters were motivated by previous work [7] in which BCG changes were effectively isolated to estimate heart rate from motion.

B. Feature Extraction

Once the waveform is obtained, we need to extract meaningful features that can be used to characterize each of the measurements. To do so, we automatically segmented the parts of the signal associated with different heartbeats, computed the average beat response, and extracted several representative features from it. This section provides more details about the different parts.

Segmentation and Aggregation. As each heartbeat is characterized by a larger motion peak surrounded by smaller ones (e.g., see Fig. 1), we located potential heart beat responses with the *findpeaks* MATLAB function (with MIN_PEAK_DISTANCE equal to the length of a heartbeat when the heart rate is 150). We then segmented the signals by taking 300 milliseconds before and 500 milliseconds after each of the previous peaks. The different segments were then averaged resulting in a specific BCG beat response. Fig. 3 shows the average responses for all the 10-second segments when using the wrist-worn gyroscope. As can be seen, there are shape differences across participants and body postures, and they are very aligned within each condition (which includes signals before and after exercising). Since previous studies have mostly relied on accelerometer or pressure sensors to monitor BCG changes, we believe this is the first time an overview of gyroscope responses is provided.

Features. In order to perform the analysis, we extracted the following types of features from the previous responses: 1) raw amplitude values, 2) histogram capturing the distribution of values (200 bins), and 3) shape features. For the shape features, we extracted the angles and distances between five descriptive points (see Fig. 1 step 3) that have been shown to vary due to different factors [1]. This approach is mainly motivated by previous research in facial expression analysis (e.g., [8]) in which angles and distances are commonly extracted between descriptive points (e.g., corners of the lips and the nose) to characterize certain facial expressions (e.g., smiling). The descriptive points were automatically detected by iteratively splitting the signal into halves and using the *findpeaks* function to obtain the maximum and minimum values of each subsegment.

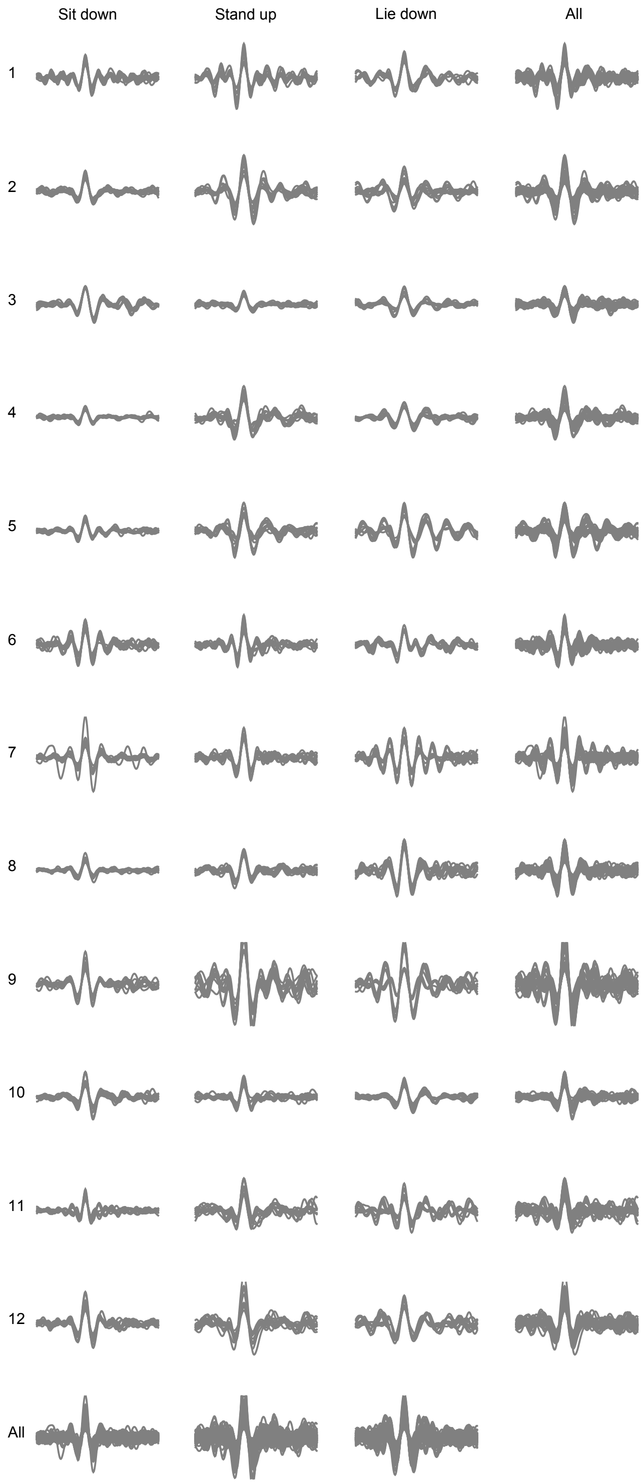

Fig. 3. Overview of average heart beat responses obtained from a wrist-worn gyroscope sensor for each participant (rows) and body posture (columns). Each combination overlays n=12 signals. The right-most column includes the responses during all the postures for each participant (n=36) and the bottom row includes all the participants' responses for each posture (n=144). The duration of each segment is 800 milliseconds.

TABLE I. PERSON IDENTIFICATION (AVERAGE ACCURACY ACROSS 100 TESTS)

Sensors	Google Glass				Galaxy Gear			
	Sit Down	*Lie Down*	*Stand Up*	*All**	*Sit Down*	*Lie Down*	*Stand Up*	*All**
Accelerometer	56.08	64.71	49.04	43.32	44.21	74.71	78.33	42.93
Gyroscope	75.79	83.21	53.29	43.38	72.21	81.50	79.04	56.54
Accelerometer + Gyroscope	**82.00**	**94.25**	**71.63**	**63.96**	**85.92**	**93.33**	**93.79**	**73.42**

The accuracy of a random classifier is 8.3%. Number of samples: 144 for all experiments except for * which was 432.

TABLE II. BODY POSTURE RECOGNITION

Sensors	*Google Glass*	*Galaxy Gear*
Accelerometer	61.11	80.09
Gyroscope	74.31	61.57
Accelerometer + Gyroscope	**80.56**	**83.33**

The accuracy of a random classifier is 33.3%. Number of samples: 432.

C. Classification

In order to assess the possibility of inferring users' identity and posture, we followed a classification approach where a subset of the data was used for training and a different subset was used for testing. For classification we used a linear Support Vector Machine with probability estimates, which allow for multiple class labels. In particular, we used the *libSVM* library which offers an efficient MATLAB implementation [2]. The misclassification cost was optimized with a 10 fold-cross validation approach on the training set. In other words, the training data were divided into 10 groups. Then, we trained on nine and tested on the tenth and repeated the process for each of the groups to find which value yielded the highest average classification accuracy. The considered values for misclassification cost were: $\log_2 C$, for C = {-10, -9, -8, ... 10}. In order to give the same relevance to each feature type, all the features were standardized to have zero mean and unit variance before training. Moreover, the dimensionality of the feature vector was reduced with Principal Component Analysis (preserving 95% of the energy), resulting into fewer than 100 components per condition.

The validation protocol was slightly different for the two problems. To perform person identification, we randomly selected 80% of the segments for training and the remaining 20% for testing. The process was then repeated 100 times to obtain average accuracy. Since each of the datasets contained 12 participants, the accuracy of a random classifier would be 8.3% (1/12). In order to perform body posture recognition, we followed a leave-one-person-out protocol, which iteratively predicts the body positions of each participant based on the data from the remaining participants. For this condition, a random classifier chance would have an accuracy of 33%.

V. RESULTS

Table I shows the results obtained for person identification when using the accelerometer, the gyroscope and the combination of both sensors, for both Glass (left) and Gear (right). Furthermore, it also shows the results when only considering segments of the same body posture (which is equivalent to previous work [6][13] for the sitting position) and when considering all of the postures (a more realistic scenario). The results during the lying down position yielded high recognition accuracy (94.3% and 93.3% when using the Glass and Gear, respectively). This finding is partly to be expected as lying down is the most constrained position and provides cleaner signals. In contrast, standing and sitting were the most challenging postures with 71.63% and 85.92% accuracy for Glass and Gear, respectively. This decrease in performance is mostly due to the impact that certain postures have on the propagation of BCG signals. For instance, during the standing position, BCG motions of the head have lower amplitude and are more influenced by involuntary body movements (see bottom graphs of Fig. 4 as an example). There was also a decrease in performance when considering all the body postures but the performance of our new approach was still far above a random classifier. Note that combining all the postures has the additional benefit of not having prior knowledge about the body position. When comparing performance across devices, the wrist located device outperformed the head mounted device. This difference may be due to a combination of different factors such as the difference in sampling rates of the devices, the appearance of more involuntary head motions during the standing positions, or the different manifestations of BCG signals on different parts of the body. A future systematic comparison examining the same type of sensors on different body locations could help identify the main factors.

Table II shows the results obtained when performing body posture recognition. In this case, both Gear and Glass could estimate the posture of participants 80-83% of the time. The two devices achieved comparable results but, interestingly, different sensors performed differently for each device. While the gyroscope worked better for the Glass, the accelerometer worked better for the Gear. We believe this is partly due to location of the sensors and the type of motions they capture. For instance, sensors on the Glass are located above the right eye where BCG movements are more rotational than linear. For all the experiments, the combination of accelerometer and gyroscope outperformed each of them when used alone, providing support that the two types of motion sensors capture complementary information.

VI. DISCUSSION

These results demonstrate that wearable motion sensors located on peripheral locations such as the head and the wrist can capture relevant information to perform person identity

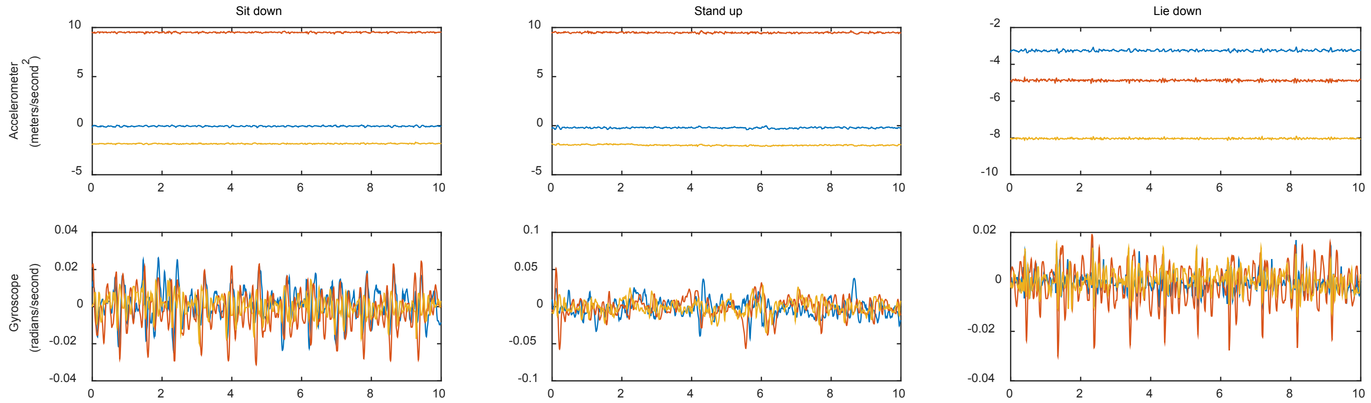

Fig. 4. Examples of raw head-worn accelerometer and gyroscope sensor data (10 seconds) during different body postures of the same participant. The average accelerometer values of the sit down and stand up postures are very similar as the orientation of the device is the same. However, subtle cardiac motions such as those observed on the gyroscope readings can be used to discriminate between the different body postures. High frequency motions shown in the bottom graphs correspond to different heartbeats.

and posture recognition, using motion data from moments when the person is relatively "still" and no large motions are observable.

The proposed approach offers several benefits that could help address some of the existing challenges of wearable devices. For instance, many wearables on the market have limited input capabilities (one single button, small or no display) to enter user ids or passwords. However, the proposed method represents an effortless way to automatically switch user identity, just by holding still for a few seconds after you put it on. Previous research efforts have tried to address this problem; for instance, Gafurov et al. [4] explored analyzing a person's gait with motion sensors to uniquely identify them. However, this approach and other research efforts mainly rely on the person moving to be able to collect enough identifying data. In practice, we see both approaches as complementary methods, as BCG signatures are more readily accessible when the person is not moving. Our approach could thus be useful to provide comfortable repeated verifications that ensure the same person is still using the system. For instance, many low-cost clinical trials that rely on pencil and paper have had their integrity questioned because of suspicions that the purported patient data was not collected from unique participants. Our new approach could validate the BCG waveform as belonging to the enrolled patient during moments of "still" data.

In the context of body posture recognition, traditional approaches usually rely on attaching one or more motion sensors to the body (e.g., [5]) where the orientation of the devices can uniquely correlate with different body postures. For instance, the average values of the different accelerometer axes of Google Glass can easily differentiate between lying down and standing up as the device orientations are orthogonal and the readings are affected by Earth gravity (see top-left and top-right graphs of Fig. 4). On the other hand, the average accelerometer readings when sitting down and standing up are very similar because the device orientation does not change. This problem occurs very frequently with wearable devices as they tend to be located on peripheral locations that can move independently of the body posture. Moreover, gyroscope sensors have been barely explored in this context as they are not affected by the orientation of the device. However, since our methods focus on monitoring subtle cardiac motions that are affected by body posture, they can effectively discriminate between these cases irrespective of the orientation of the device and the sensor modality. Our new approach offers the opportunity to more accurately track sedentary behaviors (e.g., sitting, lying, standing) with only one wristband or eyeglass form factor. Moreover, this information could then be used to enhance the landscape of contextually triggered applications in wearable devices such as activation of the step counter when standing up or enabling energy saving mode when lying down.

While these findings open the possibility of enhancing the potential applications of wearable devices in several domains (e.g., security, health tracking, personalized advertisements), they also raise serious privacy concerns. Most consumers are still not aware that wearable motion sensors can capture more personal information besides obvious motion such as steps. Also, third party applications that can be deployed on wearable platforms such as AndroidWear do not need to request users' permissions to start logging motion data. Recent research efforts have also shown that motion sensors of smartphones can capture sensitive audio signals such as the numbers of a credit card [10]. Some solutions to potentially address this problem could involve limiting the sampling rates of the sensors, encrypting sensor data, and requiring user's permission before installing applications. The work presented here demonstrates that currently commercially wearable devices can also capture personal information. Due to increased adoption of these sensors, it is critical to research and highlight the unexpected uses of wearable devices. These efforts will ensure users can be appropriately informed and privacy policies can be updated accordingly. Otherwise, malicious applications that track sensitive information without users' awareness could hinder the potential benefits.

VII. Limitations and Future Work

Our work considered data collected in a controlled laboratory setting involving two wearable devices, 12 participants, and three body postures pre-/post- exercise.

While this experiment alters the data in meaningful ways that were not considered in previous work. There are still several research challenges that need to be addressed before deploying the proposed methods in the wild.

Our study considered a limited set of classes (12 people and three body postures, respectively). Real-life scenarios are much more complex and include a larger number of classes which will require significant efforts in terms of data collection and annotation. While our approach is still limited in that regard, we believe there may be some cases where recognizing a pre-defined small number of classes may still be useful, especially in the context of wearables. For instance, devices such as Google Glass are still quite expensive and, in many cases, approved groups of people are sharing them (e.g., doctors, researchers). In this case, person identification would be a useful tool for only displaying the information of the active user, and thus helping preserve the privacy of other inactive users. Note that even though most of the devices need to be connected to another device such as the phone, most of the sensitive data (e.g., photos, notifications, e-mails) remain on the device even when disconnected. In the case of posture recognition, Li et al [9] provided a very compelling use case scenario in which a limited set of postures can be used to better track the sleep quality.

We tackled two different problems: personal identity and body posture recognition from wearable motion data. However, there is extensive literature on how other factors can also influence the BCG shapes. In our study, the range of ages was too small to account for significant changes in the BCG signals due to aging. Preliminary tests predicting gender using a leave-one-person-out validation yielded recognition rates of up to 80% while lying down and 71.67% when considering all the postures. Nevertheless, gender was strongly correlated with height (0.86) and weight (0.80), which have been shown to also affect BCG shapes. While Vural et al. [13] showed that heart beat responses were repeatable over a period of time of 1 to 2 weeks, it is still relevant to thoroughly study when and how often it is necessary to collect more data to update the classification models. In this case, online learning paradigms could potentially be very effective.

Finally, our methods rely on the person being still for 10 seconds in order to obtain a clean BCG signature. While the user could deliberately hold a position for 10 seconds to provide the information during daily life, there are already many moments in time when different parts of the body remain "still" for a certain amount of time (e.g., watching TV, reading, sleeping). For instance, in Rienzo et al. [11] researchers found that there were more than 100 5-second "still" segments per hour during the day and significantly more during the night. While their sensor location was slightly different, their findings suggest that sporadic assessments during the day without disrupting the user are feasible. Note that the proposed methods could be used in combination with existing methods (e.g., gait analysis for person identification) in order to increase the amount of potential assessments during the day.

VIII. CONCLUSIONS

Our results show a new way to extract personal information from motion-based sensors worn on the wrist or head during stationary body postures. In particular, we have shown that both the accelerometers and gyroscopes on a head-mounted and a wristband device can be used to identify the person and recognize his/her body posture in a controlled laboratory experiment. Among some of the main findings, we found that analyzing a combination of accelerometer and gyroscope outperformed each of the sensors alone, and that wrist-worn measurements provided an additional improvement in terms of accuracy. This research opens the possibility of many interesting applications such as hands-free biometric user identification and body-posture recognition irrespective of device orientation. We are looking towards a future when such applications can be used to benefit the users while keeping them informed and protecting their privacy.

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