An Early Characterisation of Wearing Variability on Motion Signals for Wearables

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ABSTRACT

We explore a new variability observed in motion signals acquired from modern wearables. *Wearing variability* refers to the variations of the device orientation and placement across wearing events. We collect the accelerometer data on a smartwatch and an earbud and analyse how motion signals change due to the wearing variability. Our analysis shows that the wearing variability can bring an unexpected change to motion signals, not only from different users but also from different wearing sessions of the same user. We also provide empirical ranges of changes in device orientations.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

wearable, motion sensing, wearing variability

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1 INTRODUCTION

Motion sensing on wearables opens up interesting possibilities of monitoring various types of everyday gestures by virtue of their fixed placement. Since they are mostly designed to be worn on a specific part of the body, e.g., a smartwatch on the wrist and a smart earbud on the ear, motion sensing on wearables can leverage the absolute orientation of the devices to monitor the fine-grained movement of a body part. For instance, a smartwatch can detect hand gestures including finger writing [12] and smoking events [6]. Dietary activities can be monitored by detecting the movement of an arm [7] and a jaw [1]. Even facial expressions such as laughing and frowning can be captured by monitoring the movement of facial muscles on an earbud [5].

Figure 1: Example of wearing variability of an earbud

While wearables guarantee the relatively fixed placement, it is still challenging to directly use raw motion signals due to a number of variability factors such as hardware variability (sampling rate heterogeneity and instability) [8] and user variability (different gesture patterns across users) [4].

We introduce a new variability factor, *wearing variability*, which refers to the variations of the device orientation and placement across wearing events. Since the device orientation affects the raw acceleration signals, it is obvious that different orientations can degrade the recognition accuracy, especially when relying on the absolute orientation of devices. It can be easily expected that different users have different wearing habits causing wearing variability. However, even for the same user, devices can be worn in different ways when the user newly wears the devices. Figure 1 shows an example (wearing an earbud from the same user); the earbud in the right figure is less tilted than that in the left figure.

While wearing variability is expected, there has been no quantification of it in the literature. Several attempts have been made for motion sensing invariant to sensor orientation [2, 9], but mostly leveraged the magnitude of the acceleration vector and targeted the physical activity recognition.

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Ustev et al. proposed an approach [11] to transform the acquired data from the sensor coordinate frame to the Earth's coordinate frame, but it requires continuous monitoring of accelerometer, gyroscope, and magnetometer, and more importantly, additional processing-heavy computation to reflect a user's facing direction. We argue that this problem demands a more principled, data-driven solution approach. We present the first ever study quantifying the wearing variability in the context of ear-worn and wrist-worn devices.

2 DATA-DRIVEN STUDY: WEARING VARIABILITY

We used two types of wearables, an earbud (eSense [3]) and a smartwatch (LG Watch Urbane 2nd version). We chose them because 1) they have commercial form factors and 2) provide open APIs to access raw sensor data. The sampling rate of an earbud and a smartwatch was set to 30 Hz and 100 Hz (FASTEST), respectively.

We collected the accelerometer data from 20 participants (16 males and 4 females) with 5 sessions. On each session, the participants were asked to naturally wear the devices as they usually do. We further asked them to stand still and put their arms perpendicularly to the ground during the collection (30 seconds). Then, they took off the devices and repeated the sessions. Note that variability of user behaviour is not the focus of this paper and thus we did not consider the situations where the participants walk or make gestures.

Looking into Motion Signals

Objective: We investigate the similarity of motion signals on different wearing events, i.e., how similar (or different) motion signals are across wearing events and users.

Setup: We segment the data streams into 3-second-long segments and measure the distance of two segments in three different ways, *intra-wearing*, *inter-wearing*, and *inter-user*. The *intra-wearing* takes two segments that belong to the same session of the participant, i.e., 4500 pairs (20 participants $\times$ 5 sessions $\times$ ${}_{10\ \mathrm{segments}}\mathrm{C}_2$). It is used as a baseline to show the stability of signals in a single session while a user is wearing the devices. The *inter-wearing* takes two segments that belong to different wearing sessions of the same participant, i.e., 20000 pairs (20 participants $\times$ ${}_{5\ \mathrm{sessions}}\mathrm{C}_2 \times 10^2_{segments}$). It shows how signals become different when a user newly wears the devices. The inter-user takes two segments that belong to different participants, i.e., 475000 pairs (${}_{20\ \mathrm{participants}}\mathrm{C}_2 \times 50^2_{segments}$). It shows how signals are different across different users; note that wearing variability also includes the cases from different users. For the distance measurement, we calculated the average Euclidean distance across sensor readings in the segment, i.e., dividing the Euclidean distance by the number of sensor readings.

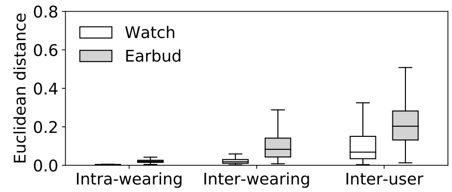


Figure 2: Euclidean distances on wearing variability

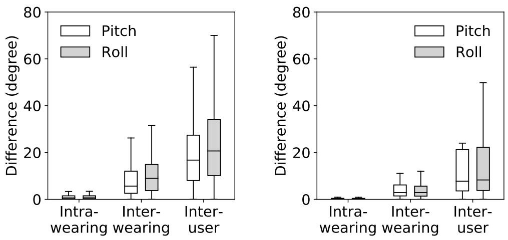
Results: Figure 2 shows the boxplots of the distances for intra-wearing, intra-wearing, and inter-user; higher distance means more different signal pattern. The results show three important implications. First, wearing variability brings a non-trivial impact on making signals look different. For example, the average distance of earbud signals is 0.023 within a wearing session (intra-wearing), 0.100 across different wearing sessions of the same participant (inter-wearing), and 0.188 across different users (inter-user). Second, the impact of wearing variability is different depending on the type of devices. While the smartwatch shows a similar pattern to the earbud, its distance increases much less than the earbud. The average distance of a smartwatch is 0.003, 0.022, and 0.040 for intra-wearing, inter-wearing, and inter-user, respectively. This was mainly because the form factor of an earbud brings more freedom of tilting as shown in Figure 1 and the amount of tilting changes even slightly every time the participant wears the earbud. On the other hand, the position of a smartwatch was relatively more fixed. Last, as expected, the distance of intra-wearing is very low on both devices; the variation of earbud signals was mainly due to the subtle movement of the head during the data collection.

Looking into Device Orientation

Objective: To better understand the meaning of the distance of acceleration signals, we further analyse the device orientation, i.e., how much the device orientation changes every time a user wears the devices.

Setup: As for the orientation information, we used pitch (rotation around the side-to-side axis) and roll (rotation around the front-to-back axis) from accelerometer readings; we did not include yaw (rotation around the vertical axis) as it cannot be measured by an accelerometer and is mainly affected by the orientation of the main body. We measured the average pitch and raw on every 3-second-long segments and computed their absolute difference between two segments.

Results: Figure 3a and 3b show the boxplots of the angular differences of the earbud and smartwatch, respectively. The results show empirical values on how much the device orientation changes due to wearing variability. For the earbud, the average difference of pitch and raw is 1.01 and 0.86 degrees for intra-wearing, meaning that the earbud hardly moved during the single session. On inter-wearing, surprisingly, the difference in pitch and raw becomes 8.36 and 8.07



(a) Earbud **(b) Smartwatch**

Figure 3: Difference of pitch and roll

degrees, respectively. The difference becomes larger on inter-user, 15.04 and 16.65 degrees. It implies that the accuracy of sensing models can be significantly dropped when they are tested on an unseen user, and more importantly, even for the same user in different wearing events.

The smartwatch shows a similar pattern, but the difference is relatively lower. For intra-wearing, the average difference of pitch and roll is 0.27 and 0.26 degrees, respectively. The average difference becomes 3.08 and 3.05 degrees for inter-wearing, and 4.27 and 4.17 degrees for inter-user.

3 CONCLUSION AND FUTURE WORK

In this paper, we systematically explored a new variability factor, *wearing variability* that needs to be taken into account for motion sensing on wearables. Our study shows that wearing variability brings an unexpected change of motion signals (compared to the reference signals used in the training), not only from different users but also the same user in different wearing events. One may argue that the impact of wearing variability looks marginal as it causes the difference of roll and pitch less than around 10 degrees. However, when motion signals on wearables are used to detect fine-grained movements of a body part with raw signals, a small difference of the device orientation can cause the significant degradation of the performance as the error accumulates while tracking. Also, note that the reported number in the previous sections is the average one. Considering the range, e.g., between from the first and third quartiles, the actual impact of wearing variability could increase much more.

Our study motivates two complementary approaches that can address wearing variability for motion sensing. First, we can leverage the data augmentation technique, e.g., [10], to generate diverse device orientations in the training dataset without further collecting the data. Our study can be used to extract a reasonable range of parameter values to cover realistic situations. Second, we can calibrate runtime acceleration data when the system detects the new wearing events. For example, the system can identify 1-second-long data when a user stands still without any movement, calculate the angular difference from the reference orientation, and rotate the runtime acceleration data, e.g., [13]. We leave them as future work.

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