CONTINUOUS INPUT FOR GESTURE DETECTION FROM WRIST-WORN WEARABLES

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Anmol Lal

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CONTINUOUS INPUT FOR GESTURE DETECTION FROM WRIST-WORN WEARABLES

Approved by:

Dr. Gregory D. Abowd, Advisor
School of Interactive Computing
Georgia Institute of Technology

Dr. Thomas Ploetz
School of Interactive Computing
Georgia Institute of Technology

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SUMMARY

Smartwatches have been readily available in markets for more than 5 years. However, smartwatches today continue to use input modalities such as touch screens, which are suitable for smartphones, but provide problems when used with small screens, such as that of a watch. Since providing input from smartwatches is cumbersome, they are used as mere extensions of smartphones. This paper presents a method to gather a continuous stream of data collected by inertial sensors of a smartwatch and smartphone to recognize different gestures as input for a smartwatch. Typical smartwatch sensors will gather data that includes movement not only of the wrist, but also that of the body. By using sensors on the phone to get the orientation of the body, the wrist-worn sensors can be used to capture the movement of the wrist relative to the body without being affected by the movement of the body. The accuracy of the calculated orientation of the wrist with respect to the body is tested and the application of the system are further discussed.

INTRODUCTION

Smartwatches, wearable devices that are placed on the wrist, are readily available in markets for consumers to purchase and use along with their smartphones. However, their usage is limited to extensions of applications available on smartphones because of the cumbersome input modalities available in smartwatches. A common use of smartwatches is to display push notifications from smartphone applications [10]. Users rely on smartphone applications for complete functionality because the smartwatch applications only provide limited features as it is difficult to provide input using a smartwatch.

One popular input modality for smartwatches is touch, but it is not ideal. Even though most smartwatches available today are equipped with touch screens, the small display size of the screens, usually 1.5 to 2.5 inches, makes them hard to use [4]. Another popular input modality is voice, but it also poses some problems. Using voice input is distracting in social situations and seems awkward in public situations [10].

Previous studies have shown that gestures, which can be detected using sensors such as 3-axis accelerometers that are already built into most smartwatches, can be used as input. Many of these studies have successfully recognized discrete sets of gestures using sensors commonly found in smartwatches to provide input from wrist-worn wearable devices [1, 5, 6, 8, 9, 11, 12, 14]. However, these techniques do not continuously track the position of the wrist. This prevents them from recognizing gestures involving continuous input. Some studies have been able to track the position of the wrist to obtain a continuous input stream, but require complicated hardware setups, are limited to certain interaction spaces or have low resolutions [2, 3, 7, 13, 15].

The current research aims to tackle these problems and develop a mechanism that, by using inertial sensors, offers a general-purpose continuous input that provides valuable information about the orientation and movement of the wrist. The continuous input obtained can be used by designers to design gestures which are suitable to use as input from wrist-worn wearables such as smartwatches.

METHODS AND MATERIALS

Hardware

This study used two Bosch BNO055 chips which have a 9-axis Inertial Measurement Unit (IMU) - containing a 3-axis accelerometer, gyroscope and magnetometer. The chip was chosen to imitate a smartwatch as most smartwatches available today have such sensors. An Android phone with a 9-axis IMU was also used. One BNO055 chip was placed in a case and attached to the wrist using wristbands to imitate the form factor of a smartwatch. The other was placed in a case and taped to the front of the belt. The android phone was placed in one of the front pant pockets.

Software

Data was collected from the chips by connecting them to the Wi-Fi hotspot of the android phone, and periodically sending data to the phone. The phone stored the data received by the 2 chips, and also its own IMU sensor. Quaternion data was collected from both the chips and the android phone at the frequency of 100 Hz. A simple moving average filter of length 10 was applied to the collected data.

Procedure

The relative orientation of the wrist with respect to the body was calculated using quaternions. A quaternion is a 4-dimensional number that can represent orientation and rotation of objects in three dimensions. A quaternion is represented by a 3-D vector that defines the axis of rotation and a number that defines the magnitude of rotation about the axis. Figure 1 shows the visualization of a quaternion, where the quaternion is rotating the vector P1.

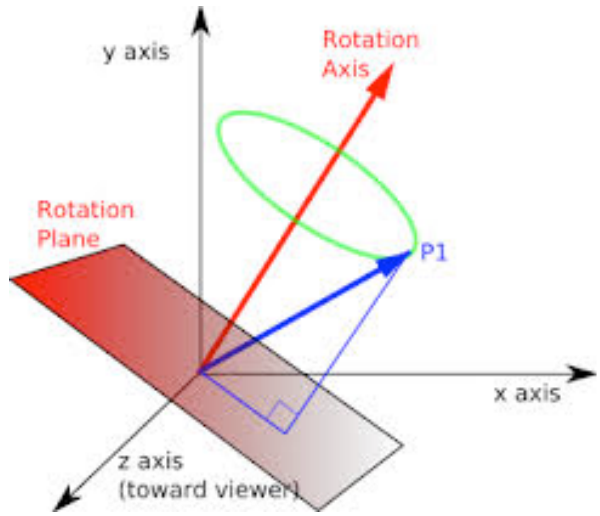

Figure 1: Visualization of a quaternion

An absolute quaternion describes the orientation of an object as a rotation applied to the three axes of the earth. Quaternions can also describe the orientation of an object relative to the orientation of another object, if the absolute quaternions of both objects are know using the following formula:

$$\text{quaternion}^{\text{relative}} = \text{quaternion}^{\text{object}}{}_1 \times \text{Inverse}(\text{quaternion}^{\text{object}}{}_2) \qquad (1)$$

The formula given above finds the orientation of object 1 relative to that of object 2. A quaternion can also be rotated by another quaternion by simply multiplying the two quaternions.

To explore whether or not a phone could be used instead of a belt sensor to determine the orientation of the wrist with respect to the body, a study with two participants was conducted. In this study, the orientation reported by the belt sensor is assumed to be the orientation of the body. Both participants were equipped with the two chips, one placed on the wrist and the other on the belt, and an android phone placed in a front pant pocket. The absolute quaternion data from these 3 devices was collected for each participant. When the data was being collected, participants were instructed to carry out natural activities as they normally do. They were not given strict instructions about which activities or gestures to perform. Using only participant 1's data, the average relative orientation of the body with respect to the phone, quaternion^{BP}, was calculated. This was done by calculating all relative quaternions of the belt with respect to the phone (using formula 1), and taking the average.

For both participants, the relative orientation of the wrist with respect to body, quaternion^{WB}, was calculated using formula 1 with the quaternions from the wrist and belt sensors. Furthermore, the absolute quaternions of the phone were rotated by quaternion^{BP} to get quaternion^{P}, the orientation of the body as predicted by the sensors of the phone. Using quaternion^{P} and formula 1, the orientation of the wrist with respect to the body as predicted by sensors on the wrist and phone, quaternion^{WP}, was calculated. The true orientation of the wrist with respect to the body is represented by quaternion^{WB}, where as the prediction of the orientation of the wrist with respect to the body using sensors placed on the wrist and phone is represented by quaternion^{WP}. The error in predicting the quaternions was calculated by finding the angle between quaternion^{WB} and quaternion^{WP}. The angle between two quaternions can be found by getting the arc cosine of the dot product of the two quaternions.

A quaternion can also be used to represent the movement of the wrist between two points in time. If the quaternion of the wrist relative to the body is $\text{quaternion}^{WB}{}_1$ at time 1 and $\text{quaternion}^{WB}{}_2$ at time 2, then the movement of the wrist relative to the body from time 1 to time 2 can be represented by quaternion^{WBR}, which is $\text{quaternion}^{WB}{}_2$ relative to $\text{quaternion}^{WB}{}_1$, and is calculated using formula 1. In this study, quaternion^{WBR} was calculated along with quaternion^{WPR}, which represents the movement of the wrist relative to the body as predicted by sensors on the wrist and phone. The error in predicting the movement of the wrist using sensors on the wrist and phone was calculated by finding the angle between $quaternion^{WBR}$ and $quaternion^{WPR}$.

RESULTS

The results indicate that the true orientation of the wrist relative to the body differed from the orientation of the wrist predicted using sensors on the wrist and phone by an average of 51.75 degrees for participant 1 and 73.77 degrees for participant 2. Figures 2 and 3 show the error in predicting the orientation of the wrist relative to the body using sensors on the wrist and phone.

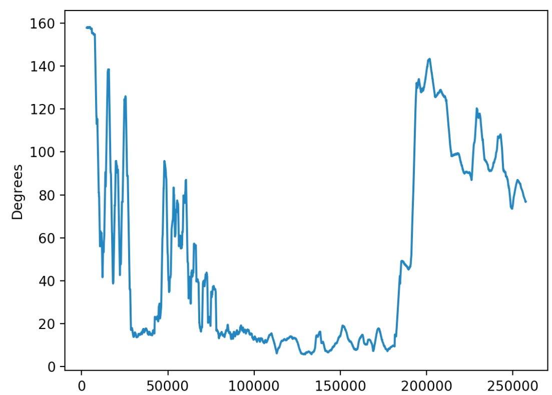

Figure 2: Error in predicting relative orientation of wrist relative for participant 1

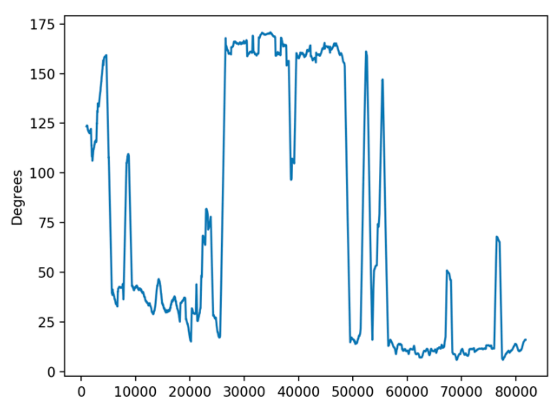

Figure 3: Error in predicting relative orientation of wrist relative for participant 2

The true movement of the wrist relative to the body differed from the movement of the wrist predicted using sensors on the wrist and phone by an average of 2.70 degrees for participant 1 and 2.88 degrees for participant 2. Figures 4 and 5 show the error in predicting the movement of the wrist relative to the body using sensors on the wrist and phone.

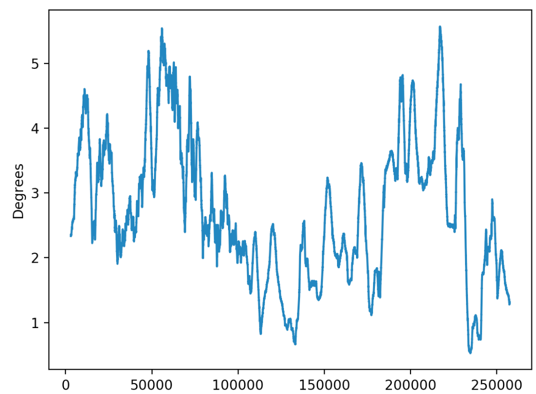

Figure 4: Error in predicting relative movement of wrist for participant 1

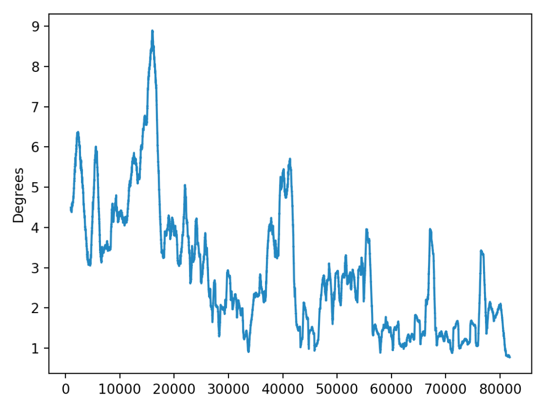

Figure 5: Error in predicting relative movement of wrist for participant 2

DISCUSSION

The results indicate that the orientation of the wrist relative to the body can not be predicted with decent accuracy using only the inertial sensors on the phone and wrist, when the phone is in one of the front pant pockets. The error in predicting the orientation of the wrist relative to the body was less for participant 1 than for participant 2. This was expected since the rotation applied to the phone, quaternion^{BP}, was calculated only using the data collected from participant 1. This method achieves poor accuracy for both participants, as the average error is greater than 50 degrees, which is too much to accurately predict the orientation of the wrist relative to the body. From figures 2 and 3, it seems like random movements of the phone in the pocket are responsible for this error. If only the rotation applied was incorrect, then the error should have been constant rather than varied. Since there is so much variation in the error, this leads to the conclusion that the phone has a lot of random movements that are not related to the movement of the body even while placed in a pocket. Another interesting finding from this study is that the average orientation of the phone may differ from person to person, as the average error between participant 1 and 2 differs by around 20 degrees. These findings lead to the conclusion that the orientation of the body can not be predicted by the phone by simply applying a rotation to the phone. Hence, this method proves ineffective in predicting the orientation of the wrist relative to the orientation of the body and can not be used for providing a continuous stream of input of relative orientation for gesture detection.

The results also indicate the the movement of the wrist relative to the body can be predicted with high accuracy using this method. The average error in predicting the movement of the wrist relative to the body was less than 3 degrees for both participants. Since gestures require movement of the wrist, this method may be useful for gesture detection by providing a continuous stream of movement of the wrist relative to the body. However, since data was only collected for two participants, the results may have been obtained by a matter of chance, and it is not certain whether or not this method can accurately capture the movement of the wrist relative to the body for most people. Furthermore, since the participants were not given strict instructions about which activities or gestures to perform, this method may only work for a specific set of activities and gestures.

CONCLUSION

Even though the orientation of the wrist relative to the body can not be predicted by only using phone and wrist sensors, the proposed method may still be useful for gesture detection as it can capture the movements of the wrist relative to the body. This method is applicable to real life scenarios as most people using smartwatches carry their phones with them, which is usually placed in a front pant pocket, which imitates the setup of the system that was tested. Furthermore, this method does not require additional hardware as the sensors used in this study are generally present in most smartwatches that are available in the market.

FUTURE WORK

This study shows that the movements of the wrist relative to the body can be determined by only using sensors on the phone and the wrist, when the phone is placed in a front pant pocket. This shows promise in the field of gesture detection for smartwatches, as it can capture the movements of the wrist with decent accuracy. As the accuracy was tested only for two participants, future work should focus on replicating the results with a larger number of participants who represent the population of smartwatch owners. Furthermore, future studies should also define a strict set of instructions which defines the activities and gestures the participants should perform during data collection. If the accuracy of this system is determined to be good by such studies, the system should be tested for gesture detection by designing sets of gestures based on the continuous input received from this system. This will determine which kind of gestures can be recognized using this method, and those that can not. Until such studies are conducted, this method is not ready to be applied in real world scenarios to collect input from smartwatches.

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