Participatory Sensing in Evaluation of Smartphone Inertial Sensors for Mobile Applications in Healthcare and Sport

Anton Kos, Anton Umek, and Sašo Tomažič
Faculty of Electrical Engineering, University of Ljubljana, Ljubljana, Slovenia
anton.kos@fe.uni-lj.si, anton.umek@fe.uni-lj.si, saso.tomazic@fe.uni-lj.si

***Abstract*—Smartphone sensors are being increasingly used in various applications in healthcare and sport. The performance of sensors varies among different smartphone models. A publicly accessible resource containing real-life-situation describing smartphone sensor parameters could be of great help for developers of applications in healthcare and sport. Therefore we have designed and implemented a participatory sensing application for measuring, recording, and analyzing smartphone sensor parameters. The application database includes sensor parameters of a number of different smartphone models. The database is offering information on several statistical parameters of the measured smartphone sensors and insights into their performance. The database of smartphone sensor parameters may prove particularly useful for developers of applications in healthcare and sport where inertial sensors are used.**

***Index Terms*—Smartphone inertial sensors, Participatory sensing, Applications in healthcare and sport.**

I. Introduction

In our modern society we are making a lot of efforts towards better quality of life (QoL). Health is definitely one of the most important aspects of someone's QoL [1]. The most straightforward way to increasing or at least maintaining the QoL is by leading a healthy lifestyle. When discussing a healthy lifestyle, two factors are predominant: a healthy diet and an appropriate amount and quality of physical activity (sport) [2].

In the era of smartphones, a great number of mobile applications in the domains of healthcare and sport are already available or are being developed [3]-[4]. The great majority of such applications use signals or data from one or more sensors that are integrated into smartphones. For example, cameras are used to measure someone's pulse signal or scan retina; signals from accelerometers and gyroscopes are used to measure, quantify, and qualify someone's movements or posture [5]; magnetometers are used to define the orientation in space; microphones are used to detect and measure environmental noise; etc.

Given a large variety of smartphone manufacturers and even greater variety of smartphone models, it is no surprise that sensor data available to applications is also of various qualities. In many health and sport applications the quality of sensor data is of crucial importance for the correct and safe operation. Bad sensor data quality could lead to injury, medical condition aggravation, or in the worst cases even to death. For example, incorrect measuring of movements in sport can lead to injury, incorrect measuring of pulse can lead to medical condition aggravation, and undetected fall of elderly person can result in death.

Considering the above said, smartphone sensor data quality for mobile health and sport applications should be checked regularly and users should be given the opportunity to verify and validate their smartphone sensors. All of the above requirements can be achieved by employment of *participatory sensing application and system* designed to measure, quantify, and validate the qualities of various smartphone sensors.

Participatory sensing applications are primarily designed for sensing physical quantities of interest, such as air pollution, temperature, body activity, and others. In these applications smartphone sensors are used to measure the values of the quantity of interest. The primary focus is on gathering the sensor data, less attention is given to the quality of the acquired sensor data.

Participatory sensing applications with high data quality demands cannot use raw smartphone sensor data. They may include intolerable measurement errors that must be eliminated or reduced before the sensor data is used by the sensing application. Our research group has been studying and developing biomechanical biofeedback systems and applications in sport based on inertial sensors [6]. Two of the several factors that contribute to the sensor errors are bias and noise. To estimate if a specific sensor is good enough for a specific application, the quality of the smartphone sensor must be known [7].

To the best of our knowledge, no study that would use participatory sensing concept for evaluation of smartphone sensor quality has yet been conducted. The results of our study are available to anyone interested, for instance healthcare and sport application developers.

Our primary motivation is to design and implement a mobile sensing application that in the first phase allows measurement, analysis, validation, and storage of smartphone inertial sensor parameters. A database of such parameters may prove particularly useful for: (a) developers of applications in healthcare and sport that would know the limitations of available smartphone sensors and (b) to the users who could at any time check or validate their particular smartphone sensors. In the second phase the database will be extended to store the parameters of other smartphone sensors relevant to the developers of users of health and sport applications. The primary contributions of this paper are:

- Validation of the participatory data acquisition concept for mass measurement and collection of smartphone sensor parameters.
- Compilation of a database containing measured sensor parameters of more than 60 smartphone models.
- Useful results and findings about smartphone sensor properties and their statistical parameters that can be the base for directions to developers of health and sport applications.
- The possibility of the identification of faulty devices that are, for example, potentially life-threatening if used in health applications.

II. Methodology and Experiment Setup

Our database is to include results for a large number of smartphone models. Participatory sensing enables acquisition of a large number of measurements in a relatively short time period; therefore it is our method of choice. The quality of smartphone sensors is limited by sensor inaccuracy and imprecision. Sensor bias and noise cause parameter value errors that induce the linear angular error of gyroscope and quadratic position error of the accelerometer [6].

A. Basic sensor property calculation

Sensor bias of the signal x is defined as an average sensor output at zero sensor input and it is estimated by averaging N samples of sensor signal (1).

$$x_{bias} = \tfrac{1}{N}\sum_{n=0}^{N-1} x[n] \tag{1}$$

The bias estimate averaging time depends on sampling frequency f_s and signal sample block length N. Bias estimate exhibits variations which are the result of a sensor noise. Sensor noise characteristics can be observed by measuring the Allan variance (3) that is defined as the average squared difference between successive bias estimates $y[m]$ (2). Each $y[m]$ is calculated from a block of N signal samples.

$$y[m] = \tfrac{1}{N}\sum_{n=0}^{N-1} x[n + m\cdot N] \tag{2}$$

$$\sigma_A^2[N] \approx \tfrac{1}{2\cdot(M-1)}\sum_{m=1}^{M-1}\left(y[m]-y[m-1]\right)^2 \tag{3}$$

Our application calculates the bias estimates of the sensor, Allan variance, Allan deviation σ_A at T_{avg} = 1 s and noise parameters. Allan deviation is also known as velocity random-walk parameter for accelerometer and angular random-walk parameter for gyroscope.

B. Experiment setup

We have implemented a pilot system that employs the participatory sensing concept, where participants are actively engaged in the data collection. The participants connect their smartphones to one of the available wireless networks and send sensor data to the server in the internet, see Figure 1. The server extracts the measured sensor parameters and writes the anonymized results into the database. Participants can use the database access to check their personal results or various statistics. The pilot system is designed for a medium group of advanced smartphone participants.

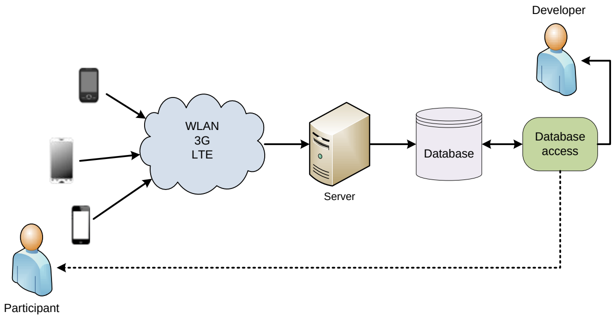

Figure 1. Participatory system architecture. Smartphones send sensor data over one of the available wireless interfaces to the processing computer (server). Processing results are stored in the database. They can be analyzed and retrieved through a database access application.

The participant needs to install and setup one of the supported off the shelf applications that have the option to stream sensor data to a remote location: (a) for the Android platform the Sensor Node version 1.53; (b) for iOS platform Sensor stream version 1.1 and Sensor monitor (Pro) version 1.0.9. Each sensor measuring episode must be actively started by the participant. By starting the measuring episode sensor data is sent to the server and anonymized results are written to the database. The server is in the public IP network and it is running the custom-designed LabVIEW™ application. The database used is XAMPP mySQL running on Windows server 2008 R2. For the retrieval of the participant's smartphone measuring results, PhoneID is required.

III. Results

Our measurement and data collection campaign lasted 44 days and during that period we were able to gather results of 61 different smartphone models from 13 different manufacturers. We collected more than 500 measurements from 116 different smartphone devices. Some smartphone models are represented in the results by several different smartphone devices. Most of the smartphone devices were measured once, but readily accessible devices were measured several times, some of them even continuously throughout the measuring campaign.

A. Complete dataset results

We present the complete measurement dataset in graphs and tables. Figure 2 shows smartphone accelerometer biases for all the measured devices and Figure 3 shows smartphone gyroscope biases for all the measured devices. Plotted values represent the measured parameter values by the device.

Accelerometer and gyroscope biases are measured under conditions defined in Section II.A. The averaged accelerometer biases for all devices under test are shown in Figure 2 and averaged smartphone gyroscope bias measurements in Figure 3. Some devices have large bias, but they are not necessary faulty. For example, excessive gyroscope bias values are evident in the results of the device with ID = 73 in Figure 3.

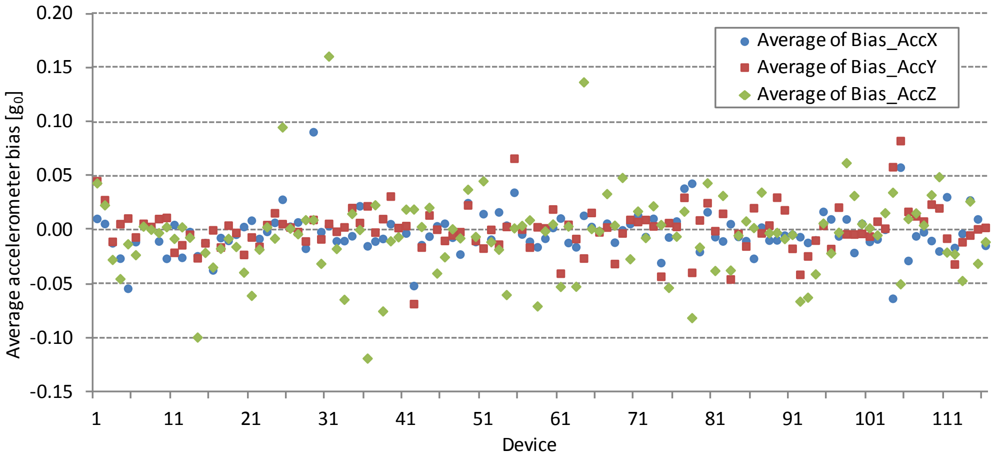

Figure 2. Average accelerometer biases of 116 different smartphones for X, Y and Z axes. The horizontal axis represents the device identification number (ID) from the measurement database.

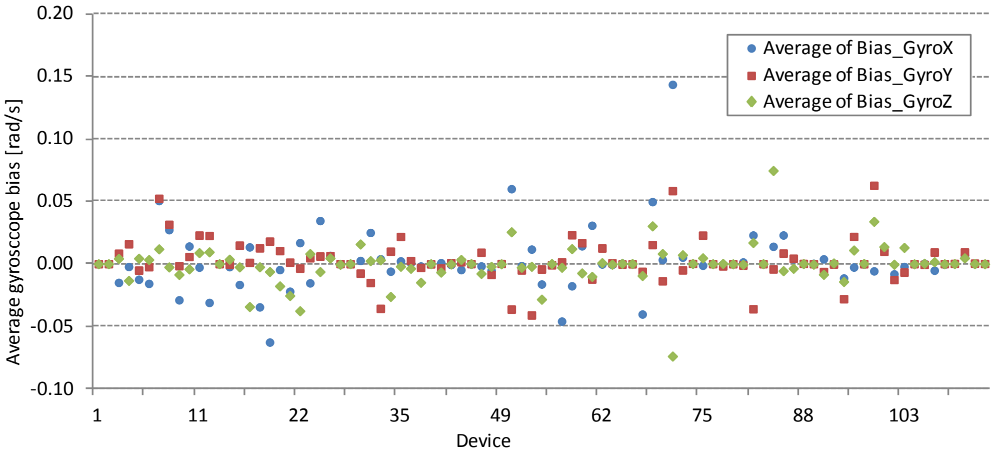

Figure 3. Average gyroscope biases of 116 different smartphones for X, Y and Z axes. The horizontal axis represents the device identification number (ID) from the measurement database.

B. Results by smartphone model

While statistics of the complete measurement dataset gives us the overall picture of the smartphone sensor statistics, it is sometimes more interesting to show only the results for a particular smartphone model. In this subsection the statistics of different smartphone models are presented and compared. Only the smartphones with enough physical devices of the same model have been taken into consideration. The selection includes eight popular smartphone models: Galaxy S3, Galaxy S4, iPhone 4, iPhone 5, iPhone 5S, iPhone 6, Nexus 5, and Xperia Z1 Compact.

For illustration we group the dataset of properly working devices shown in Figures 2 and 3 by the smartphone model. The comparison is done for the popular smartphone models listed in the previous paragraph. At least six different devices of the same model are measured. Figure 4 shows the comparison of the averaged accelerometer noise density in combination with its standard deviation.

Results in Figure 4 are presented in the random order. Similar differences in sensors noise parameters between various smartphone models are evident for all principal axes. Smartphone models with codes 4 and 8 exhibit the best performance of accelerometer sensor.

C. Results of individual smartphone device

The results of the complete dataset and statistics by model, presented in Sections III.A and III.B, are particularly useful for health and sport application developers. Individual participants may find these results useful when comparing their smartphone device to all the smartphones measured or to the smartphones of the same model, brand, operating system, etc. But participants, who measure their device repeatedly, over some period of time, can benefit also from the statistics about their own device. Figure 5 presents one such case when one of the participants is measuring his/her device repeatedly daily 44 times. The plot presents the device's gyroscope bias given in [rad/s]. It can be observed that the bias is in general quite stable with slight variations during the measured period.

A large number of bias measurements for the same sensor device can give some information about one of the most important sensor parameter; bias variation. Accelerometer and gyroscope biases vary with time. Bias variations are the result of random, low-frequency sensor noise and of deterministic dependence on temperature fluctuations. Deterministic bias drift cannot be compensated without measuring of sensor temperature.

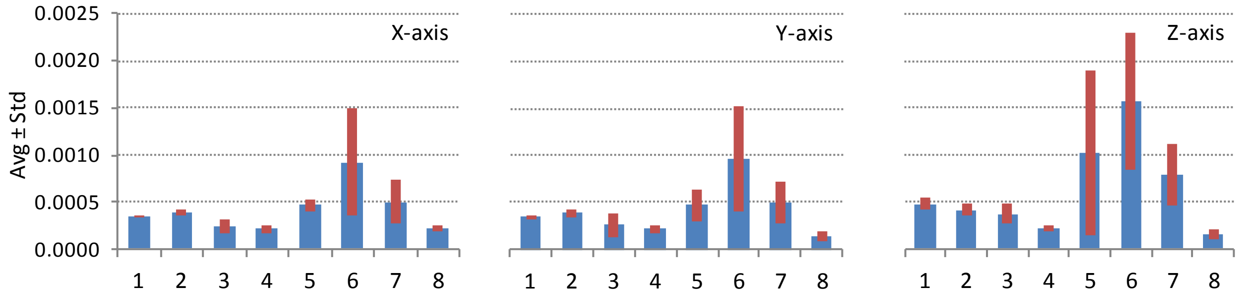

Figure 4. Comparison of average accelerometer noise parameter and its standard deviation for eight different smartphone models. Smartphone models presented are: Galaxy S3, Galaxy S4, iPhone 4, iPhone 5, iPhone 5S, iPhone 6, Nexus 5, Xperia Z1 Compact. The listed smartphone models are presented in a random order (the same for all graphs). The vertical axis shows noise in [$g_0/\sqrt{\mathrm{Hz}}$].

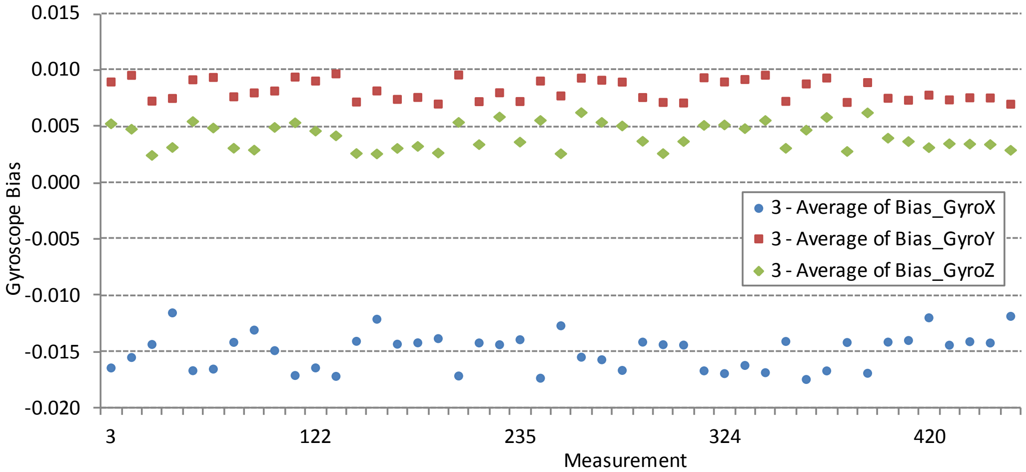

Figure 5. Repetitive measurements (N = 44) of the gyroscope bias given in [rad/s] of the smartphone with ID = 3 showing bias variation. Measurement numbers are taken from the database and are not successive as other measurements took place in between two measurements of the presented device.

IV. Conclusion

The results of our pilot implementation are interesting and encouraging. Even in this limited volume, they can prove useful to developers of healthcare and sport applications.

A developer of a health or sport application can benefit from such results in several ways. For example, knowing that different applications require different levels of sensor quality, that bias can be compensated, and that noise can only be reduced, but not eliminated, a developer may choose different approaches. For example, if the application requirements are low, the developer may decide not to compensate biases at all, providing that the targeted group of smartphones exhibit biases that satisfy application requirements.

Larger scale measurements would give us a better overall picture of existing smartphone sensor's performance. Its results would form a basis for further research in this field, such as data mining, and offer a good reference for the development of smartphone sensing applications.

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