Limitations of Smartphone MEMS for motion analysis

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***Abstract*—The paper presents the limitations of smartphone motion sensors and their suitability for simple biofeedback applications with motion detection. We have measured the smartphone accelerometer and gyroscope biases, identified the main causes for short-term and long-term bias variations, and quantified their precision. Under certain conditions the existing smartphones with their built-in inertial sensors are suitable for use in real-time biofeedback applications.**

I. Introduction

Smartphones are readily available, wide-spread technology. According to [1] in many countries the penetration of smartphones has exceeded 50% in 2014. Practically all new smartphones available today are equipped with MEMS (Microelectromechanical systems) sensors, which are mostly low cost sensors and consequently of relatively low quality. Their use for motion tracking is limited due to their low quality which is expressed through the imprecision of sensor signals. MEMS accelerometer and gyroscope quality is mostly degraded by bias, noise and nonlinearity. Several calibration methods can improve the sensors precision, which is mostly affected by their biases . Most basic calibration method include sensor bias measurement and compensation. For an application developer the exact specifications of the inertial sensors integrated into smartphones are not always well-known. There are several different possible reasons for that, for example: specifications are not available, application runs on different hardware (android smartphones), or sensor readings are preprocessed inside the smartphone's operating system. Even if the inertial sensor specifications are known, it is reasonable that an application using them has functionality for the measurement of their properties. Measured values give us the ability to act in cases when the sensor precision is outside the bounds required by the application.

Our first goal was to explore the suitability of inexpensive inertial sensors integrated into today's smartphones for the development of a real-time motion biofeedback system. In a *biofeedback* system application user has attached sensors for measuring body functions and parameters (*bio*). Sensors signals are transferred to signal processing device and results are communicated back to the person (*feedback*) through one of the human senses (i.e. sight, hearing, touch) [2]. The person tries to act on received information to change the body motion in the desired way. As an example of a real-time biofeedback system we designed an application that helps users to correct specific golf swing errors [3]. The application uses the inertial sensors integrated into the smartphone, which is attached to the head of the golf player. With the appropriate attachment of the inertial sensor to the cap of the golf player, we can achieve very good repeatability of detection of different 3D head movements.

II. Bias Measurements

In our experiments we used iPhone 4 smartphones. As identified by Chipworks [4] and [5], the iPhone 4 embedded 3D gyroscope and 3D accelerometer integrated circuits are manufactured by STMicroelectronics. Main iPhone 4 sensor parameters, acquired from the manufacturer's data sheets [6] - [8] are listed in Table 1.

TABLE I.
THE MAIN PARAMETERS OF THE IPHONE 4 MEMS [6]-[8].

Parameter	3D accelerometer LIS331DLH	3D gyroscope L3G4200D
Range	±2 g	±2000 deg/s
Sensitivity	1±0.1 mg/dig	70 mdeg/s/dig
Bias error	±20 mg	±8 deg/s

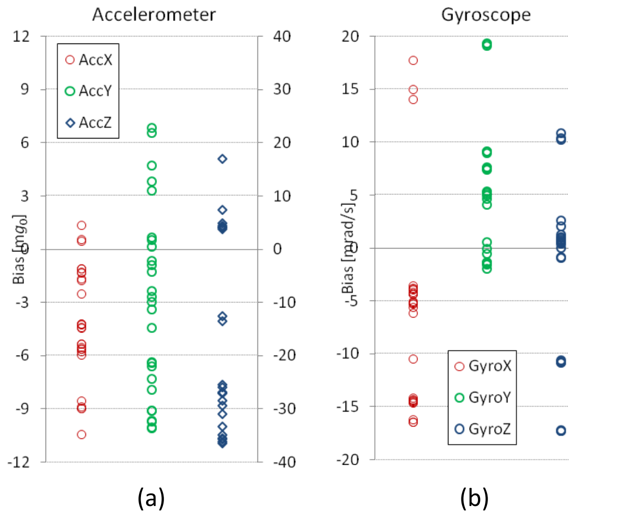

Figure 1. 3D accelerometer (a) and 3D gyroscope (b) biases gained from multiple measurements on several smartphones. Biases are calculated by averaging $N = 600$ sensor signal samples at sampling frequency $f_s = 60$ Hz, the corresponding averaging time is therefore $\tau = 10$ s. Accelerometer biases presented in mg_0 have different dynamic ranges and are presented on two separate scales; the left hand side scale is valid for X and Y axes, and the right hand side scale for the Z axis. Gyroscope biases, presented in mrad/s for all three axes, have similar dynamic ranges and are presented on the same scale.

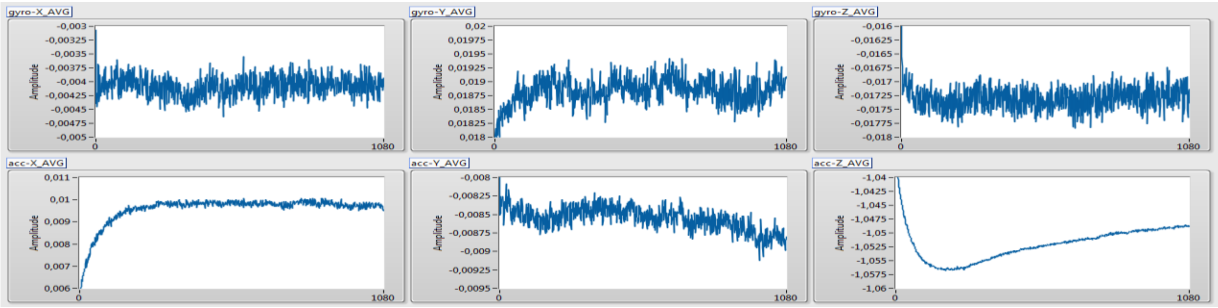

Figure 2. Measured bias values in the 3 hour temperature stress test. Each bias value is gained by averaging 600 sensor signal samples in 10 second intervals. Therefore 1080 bias values shown in graphs are gained in the 3 hours long test. Temperature changes induce noticeable bias drift of accelerometers and gyroscopes.

The precision of smartphone sensors is mostly affected by their biases, which induce errors in the derived angular and spatial position [9], [10]. There are other factors that influence the sensor precision. For example, a simple and computationally efficient calibration procedure for sensor axes misalignment is presented in [11].

For the estimation of the bias value ranges we have conducted a series of measurements on a number of iPhone 4 smartphones in different time intervals. Bias measurements were carried out with the specially developed application running in LabVIEW and using the specially designed and constructed casing allowing us to orientate the smartphone in any of the principal positions in a simple way. The aim of this measurement results is to present the bias variations on different smartphone devices of the same type (iPhone4).

The measurements were performed in twelve positions to eliminate the influence of the gravity. The application receives sensor data from the smartphone over the local wireless network and calculates a range of statistical parameters of smartphone inertial sensor signals. Bias measurement results for six iPhone 4 smartphones are shown in Fig. 1. Measurements for all three accelerometer and gyroscope axes are averaged over the time interval τ = 10 s. The gained gyroscope biases are within the range of $\Delta G_0 = \pm 20$ mrad/s = ±1.15 deg/s. The gained accelerometer biases are within the range $\Delta A_0 = \pm 12$ mg$_0$ for the X and Y axes, and $\Delta A_0 = \pm 40$ mg$_0$ for the Z axis.

While the differences between devices are the effect of variations in physical properties of MEMS [8], the differences in successive measurements of the same device are caused by various inertial sensor instabilities, most probably because of slightly different internal phone temperatures between measurements. To test our assumptions, we conducted a simple temperature stress test. First, we have cooled the switched-off smartphone down to 8°C. After switching the phone on and putting it in the place with the room temperature of 22°C, we have measured biases in time periods of several hours. The bias drifts, shown in Figure 2, exhibit the strongest temperature dependence in the first 30 minutes of the test. During this time interval the temperature changes induce bias drifts that can be much larger than the bias variations caused by other factors of sensor instabilities, including noise. In the measurement of a particular smartphone, shown in Fig. 2, the latter is especially evident in the bias drift of the accelerometer axes X and Z. The results of stress test measurements on other smartphones show that strong temperature induced bias drifts are expressed also on other exes. Temperature stress tests show that the change in temperature, as it was anticipated, causes large bias variations, especially for accelerometers. Stable temperature conditions are reached after 60 minutes.

Bias variations measured in constant room temperature conditions are much smaller. The same measurements were carried out in the 60 minutes period on six different smartphones; each bias value is gained by averaging the 600 sensor signal samples in 10 second intervals. Accelerometer bias variations due to noise are in the range of 0.35 to 0.5 mg$_0$. Gyroscope bias variations due to noise are in the range of 0.7 to 1.0 mrad/s. Larger differences between smartphones are expressed in bias drifts. Gyroscope bias variations are primarily the result of the sensor white noise. In most cases the measured bias drift is comparable to the averaged bias noise. Less often the bias drift is higher than the averaged bias noise (τ = 10 s). In the worst case, the measured gyroscope drifts stay below 2 mrad/s per hour and the measured accelerometer bias drifts do not exceed 4 mg$_0$ per hour.

A. Allan variance measurements

Bias variations are caused by various random processes in the operation of the sensor. The Allan variance method helps us to determine the characteristics of the underlying random processes and noise models.

Biases are measured by averaging a finite sequence of samples when the device is in the standstill position. Bias approximations $y[m]$ are calculated by averaging the sensor signal samples $x[n]$:

$$y[m] = \frac{1}{N}\sum_{n=0}^{N-1} x[n + m \cdot N] \qquad (1)$$

Allan variance $\sigma_A^2(N)$ is a measure of variations of mean values $y[m]$ of the consecutive blocks of N signal samples $x[n]$ [12]:

$$\sigma_A^2\,[N] = \tfrac{1}{2}\overline{(y[m] - y[m-1])^2} \qquad (2)$$

The approximation of the variance is calculated from the finite number of mean values $y[m]$:

$$\sigma_A^2\,[N] \approx \frac{1}{2\cdot(M-1)}\sum_{m=1}^{M-1}(y[m] - y[m-1])^2 \qquad (3)$$

Gathering the data for Allan variance calculation $\sigma_A^2(\tau = N\,T_s)$ requires long measurement times τ and also a large number of signal samples $x[i]$. The upper averaging time was set to τ_{max}=1000 s. Allan variance measurements are performed simultaneously for five different averaging times τ = {0.1, 1, 10, 100, 1000} s. The maximal averaging time requires N_{max} = 60000 signal samples. For a statistically relevant measurement the minimum number of averaging episodes must be M_{min} = 10. Therefore the total measurement time T_0 = 10000 s.

Depending on the nature of the random process, the bias noise has different power spectrum shapes. Noises with different spectrum power density profiles appear in the Allan variance plot with different slopes [12]. In such situation it is possible to identify the model of the underlying random process from the Allan deviation σ_A(t) log-log plot, where different noises appear in different regions of τ. Allan variance measurements of the 3D accelerometer and 3D gyroscope for a single smartphone are shown in Fig. 3. As shown in Fig. 3(a) the accelerometer Allan deviation σ_A(t) is following the slope of the bias white noise model at short averaging times τ ≤ 10 s. Accelerometer *velocity random walk* constant (VRW) can be determined from the Allan deviation plot at τ = 1 s; VRW = σ_A(τ = 1 s). Model parameters for all three axes are given inside the shaded rectangle in Fig. 3(a).

As shown in Fig. 3(b) the gyroscope Allan deviation σ_A(t) is following the slope of the bias white noise model at short averaging times τ < 100 s. Gyroscope *angle random walk* constant (ARW) can be determined from the Allan deviation plot at τ = 1 s; ARW = σ_A(τ = 1 s). Model parameters for all three axes are given inside the shaded rectangle in Fig. 3(b). At longer averaging times, where the averaging filter decreases the power of high frequency white noise, slow bias fluctuations with accented low frequency spectrum becomes the dominant error source for accelerometers and gyroscopes. Log time resolution measurements at τ = {0.1, 1, 10, 100, 1000} s in Fig. 3 allow only the determination of the minimal bias instabilities (BI), which are expressed at τ = 100 s for the accelerometer and τ = 1000 s for the gyroscope.

Measurements were conducted under the conditions of the stable smartphone operation: constant room temperature, absence of vibrations, and low and constant power dissipation of the smartphone. The same measurements were performed on six different iPhone4 devices. We have noticed only minor differences in noise models. The calculated average sensor parameters are: VRW = 0.26 $mg_0/\sqrt{Hz}$, ARW = 26 $mdeg/s/\sqrt{Hz}$. More noticeable are the differences in the bias instability, which are to our belief primarily the effect of different temperature sensibilities of the smartphones.

On the basis of the average sensor model we can determine averaging times τ for bias measurement that is used as offset value at sensor bias compensation. We conclude that the reasonable averaging times for bias measurements are between 10 s and 100 s.

B. *Bias estimation error*

The measurements of accelerometer and gyroscope biases on several smartphones indicate that some particular applications with moderate demands for accuracy and short time analysis could use even uncompensated sensor data. From Fig. 1 we see that gyroscope biases are less than 1 deg/s, and accelerometer biases are below 40 mg_0. Uncompensated bias values are inducing *bias error (1)* from Fig. 4(b). For the *uncompensated gyroscope* this means that in a short time analysis, for instance in a 3 seconds interval, the bias induces angular error of less than 3 degrees. Relatively high accelerometer biases restrict the use of *uncompensated accelerometers* for position tracking, but for the calculation of the tilt angle between a smartphone's axis and the gravitation vector, the error is less than 2 degrees.

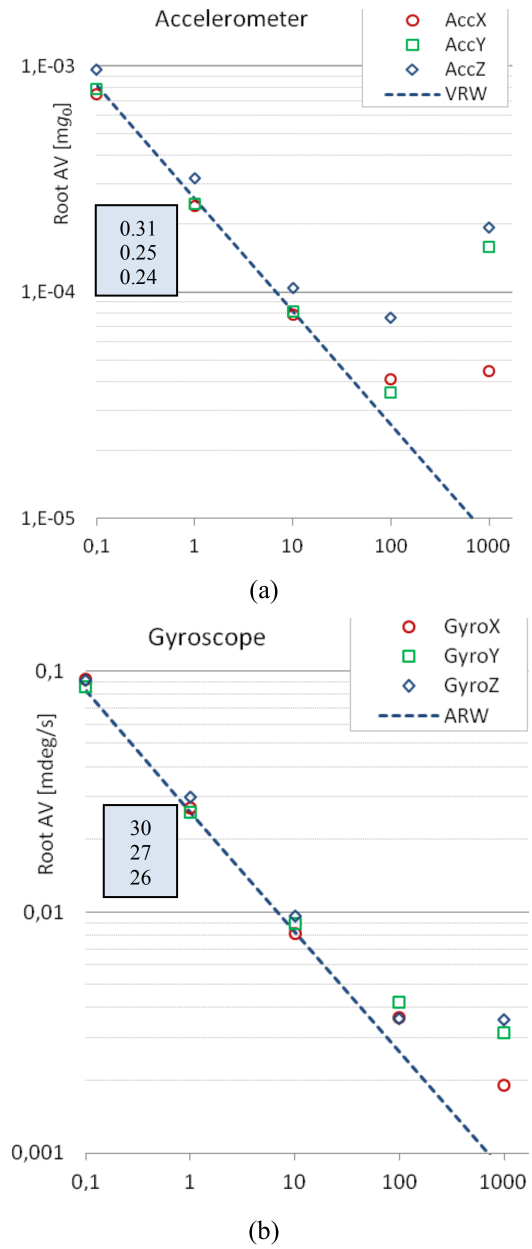

Figure 3. Allan variance measurements for all three axes of the accelerometer and gyroscope of the single smartphone. (a) Accelerometer results conform to the VRW model at short averaging times. (b) Gyroscope results conform to the ARW model at short averaging times.

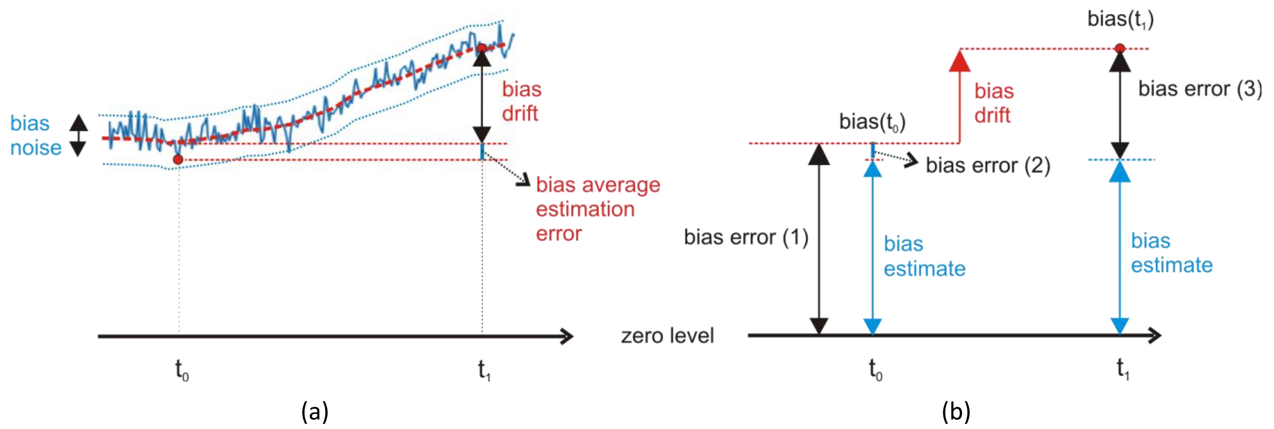

Figure 4. Inertial sensor bias variations and their effects. The measured bias changes with time (blue line), in the short time primarily because of bias noise (ARW, VRW), in the long term because of other influences (red dashed line). The instantaneously acquired bias estimation value at the time t_0 (red dot) can differ from real bias for the estimation error (the difference between the parallel red dotted lines). Bias drift is the change in bias value between times t_0 and t_1. (b) Bias error is the difference between the *zero level* and the real bias value. Without compensation we experience *bias error* (1), with the compensation at time t_0 we decrease the bias error for the measured bias estimate to get *bias error* (2). By the time t_1 the bias drift causes the error to grow to the value of *bias error* (3).

The precision of the accelerometer and the gyroscope is considerably better after bias compensation. The compensated bias values at time t_0 are inducing bias error (2) from Fig. 4. Gyroscope bias compensation can be performed in a smartphone's standstill position. Based on Allan variance results from previous section, the sufficient averaging time τ = 10 s. This gives us a good compromise of the noise elimination and bias instability influences. Accelerometer bias compensation requires several successive measurements in precise rotations around the three axes. Consequently the compensation of the accelerometer takes much more time and effort.

The calculated variation of the mean bias values is ΔG_0 = 25 mdeg/s for the gyroscope and ΔA_0=0.25 mg$_0$ for the accelerometer. That means that 3 seconds after the bias compensation the maximal angular drift is 0.075 degree and maximal position drift is 1.1 cm. According to Fig. 4., the above values are valid only shortly after the bias compensation at time t_0. If we perform the same analysis at time t_1 the expected angular and velocity drift would be higher because of bias drift that would result in *bias error (3).* If a new bias error is not acceptable for the application, another bias compensation procedure should be performed at time t_1.

III. Bias Compensation Options

Inertial sensors bias variations in the form of noise and drift could be the limiting factor for their usability in different types of applications. In the biofeedback applications, where we generally use inertial sensors to measure movement patterns, large biases are a limiting factor. The precision of the sensor readings can be improved to a certain extent by bias compensation, but we have to bear in mind that bias errors can never be fully eliminated as it is evident from Fig. 4. With regard to each individual application and its demands for sensor precision, we must choose the correct bias compensation strategy:

- *One-time, single bias compensation* has a time-limited effect. Therefore a one-time compensation is suitable only for applications that operate in a stable environment. Periodic bias measurements on the same smartphone, in long time intervals over several weeks, showed that estimated gyroscope biases vary for less than 30 mdeg/s and the estimated accelerometer biases vary for less than 1 mg$_0$.
- *Periodic, repetitive bias compensation* can be performed in regular time intervals or on as needed basis. For instance, the bias compensation is needed at every significant change of the inertial sensor temperature. This temperature change can be caused by the change of the ambient air temperature or by the change of the inner temperature of the smartphone. In our experience, confirmed by the measuring results, the change in the inner temperature caused by running applications causing the heating of other hardware and integrated circuits of the smartphone, has greater and more instant effect than the change of the ambient air temperature.

To achieve different levels of movement detection accuracy the following strategies are possible:

(a) The application uses *uncompensated sensor data*. In this case the bias error corresponds to the *bias error 1)* in Fig. 4. The derived angle and position errors, as measured in previous section are 1 deg/s and 19 cm after the first second respectively. This compensation scenario could be applicable to short time movements, up to a few seconds long, if the application does not use accelerometers for position calculation and does not demand high angular precision.
As an example, signal analysis in our golf swing biofeedback application takes less than 3 seconds. Predicted gyroscope angular error in such short time

interval is less than 3 degree. Static position angle (tilt) is calculated from accelerometer data and maximal tilt error in vertical position is less than 2 degrees.

(b) Before use, the application performs a *one-time bias measurement and compensation* of the accelerometer and the gyroscope. In this case the bias error corresponds to the *bias error (2)* in Fig. 4. The effect of one-time compensation is satisfactory if the operating conditions do not differ much from the conditions at which the compensation was performed. In such cases biases change in a very limited value range. The derived angle and position errors, as measured in previous section, are 25 mdeg/s and 1.2 mm after the first second respectively. This compensation scenario could be applicable to short time movements, up to a few seconds long, even for the applications demanding high precision or for the medium-time movements, up to a few tens of seconds long for less demanding applications. When the operating conditions change considerably, new bias measurement must be carried out and if needed compensated.

One-time accelerometer and gyroscope bias compensation have significantly improved angle precision in our golf swing real-time biofeedback application. For a short time after the bias compensation both angular errors stay negligible small: vertical positioning (tilt) error is less than 15 mili-degrees and gyroscope rotation angle error in three seconds long time interval is less than 0.08 degree. Biases drifts and after one hour enlarges both angular positioning errors: vertical positioning angle error is less than 0.25 degree and predicted gyroscope rotation angle error is less than 0.35 degree.

(c) The application *constantly measures and compensates biases*. Compensation of gyroscopes is possible during the application use, while the compensation of accelerometers require temporary interruption of application use. At every detected opportunity, when the device is in standstill long enough, the gyroscope biases are measured, evaluated and if needed compensated. The measurement times required for this compensation scenario could be between 10 s and 100 s. After a longer time period without compensation, the application may notify the user that the accuracy of the operation might be compromised and that a new bias compensation is required.

IV. CONCLUSION

Our study shows that under certain conditions the existing smartphones with their built-in inertial sensors are suitable for use in real time biofeedback applications. We have studied accelerometer and gyroscope biases, identified the main causes for short-term and long-term bias variations, and quantified their precision. The uncompensated smartphone sensor biases are in the range of ±40 mg_0 for accelerometer readings and in the range of ±1 deg/s for the gyroscope readings. These values restrict their use in biofeedback systems to short analysis window, up to a few seconds long. Bias compensations can significantly broaden the range of sensor usability, both in the prolonged analysis times and in higher precision required. The compensation using averaging times between 10 s and 100 s primarily eliminates the sensor's white noise. It reduces the bias by the factor of magnitude. The long-term bias variations caused by temperature changes may remain a problem.

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