The effects of hardware and software-based signal distortion in multi-platform indoor positioning systems

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Abstract. With the constant platform fragmentation in the global smartphone and tablet market, providing a multi-platform indoor positioning technology is and ever more complex task. RSSI-based hybrid indoor positioning technologies provide hope for a unified indoor positioning solution without the need for calibrating each and every device manually before use. But differing antenna construction, sensor designs and differences in software provide measurement readings that are challenging to compare and thus make the development of multi-platform indoor positioning solutions challenging.

The different hardware and software platforms on a wide array of hardware provide massively differing measurement readings on a number of sensors essential for indoor positioning. Magnetometer, accelerometer and gyroscope readings from a multitude of devices are presented all measured from a custom-build software infrastructure designed to provide comparable readings on different platforms.

Keywords. Indoor positioning, RSSI, Wi-Fi, Bluetooth, accelerometer, gyroscope, magnetometer, magnetic field sensor, signal strength, hybrid positioning systems

1. Introduction

In these last years there have been many attempts to solve the problem of indoor navigation on different platforms, but such a solution has not yet been revealed which is really platform-, manufacturer- and sensor-independent. The drawback of most of these solutions is that such specifica-

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tions must be met that exclude some devices. There have been many attempts to solve indoor positioning with the help of Wi-Fi, which has numerous disadvantages. Suffice to say that how much distortion the scattered signals cause when locating the exact position. Of course it's possible to filter interference cause by scattered signals with the help of different algorithms (e.g. Kálmán filter), but it would require so much resource and computational capacity that it would become uneconomical.

Also RFID proved to rule out fewer devices. However, in this case the problem is that it needs a special sensor, which is only built in the latest generation smartphones as standard equipment. But the spread of such devices will take years. These were only two examples showing how present solutions fragment the mobile market in the terms of indoor positioning.

Our goal is to develop a platform-independent method that would operate on most smartphones. But first we need to aware of the qualities and sensitivity of the sensors in devices.

2. Material and Method

2.1. Hardware and Software

In our present research we analysed the sensors of devices with the help of the software developed by Lanoga Kft. It can record data sensed by the accelerator, gyroscope and magnetometer. At the beginning of the measurement it defines the exact location, then we can choose which sensor we would like to use. Before the start of the measurement the sampling frequency is adjustable.

Measurement activities were conducted with the following sensors of all of the below-mentioned devices in 30 second intervals with a frequency of 10 measurements per second.

We conducted our measurements with the following devices: Google Nexus 5 (Android 4.4.4), Nokia 1020 (Windows Phone 8.10328.78), HTC One Max (Android 4.4.4), HTC 8X (Windows 8.1). The software screenshot is shown in Fig. 1.

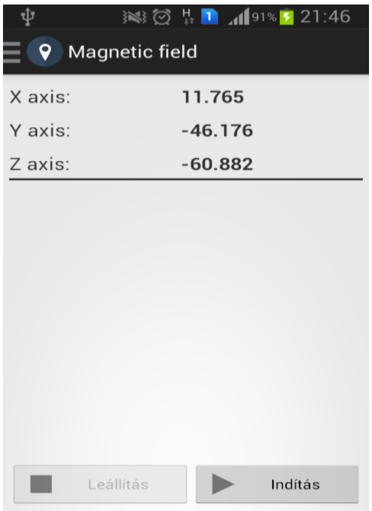

Fig 1. Software applied in the measurements

As it can be seen on the graph the software captures the data of the magnetometer thus determining the spatial position of the device. After the measurement we can export the data to an excel file, hence their processing starts here. During our measurements we collected nearly 120.000 records from different test areas.

2.2. Test area

The measures were done in a classroom and in the dormitory hall of University of Pécs, Hungary. For each measure no other electric or interference-causing device were running in the room to make an influence to the magnetometer (G Tejada et al 2013). A room with four corners (A, B, C, D) was chosen to be our test area.

In addition there was no other active device during the measurement activities to avoid any interference in order to ensure the accuracy of raw data as much as possible.

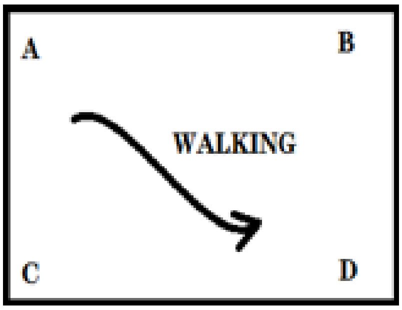

Fig. 2. The classroom measuring area

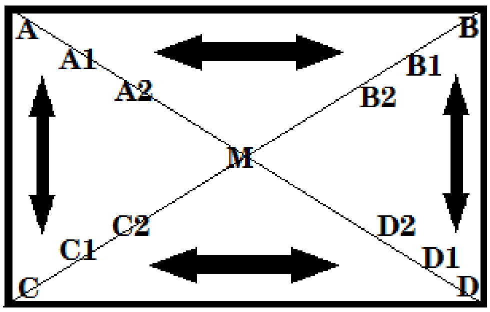

Fig. 3: A more detailed measure taken indoors

First we measured the corners in the room. The corner settings are as Fig. 2 and 3.

We collected data from corners A, B, C and D while walking with the phones for both the dormitory and the classroom. The second time, in order to distinguish among the statistical characters we completed measurements with the phone moving and being stationary. The latter gave more precise results. the following measure method is designed as Fig. 2 and 3. Measures were done walking from A to D, then from A1 to D1, and from A2 to D2, M being the centre of the room; as well as walking with the phone on the path A-B, B-D, D-C, C-A and back and forth between the corners.

In this paper we are following the methodology proposed by Galván-Tejada et al.[12] to obtain indoor location. The process consists of five steps

Several notable results[12, 13] in using a single device for wireless fingerprinting-based indoor localization exist, the most promising ones use K-nearest neighbours, Bayesian classification method, Decision trees or Kálmán filter, to name just a few. To extend any model to several hardware platforms without the need for training the algorithm for hundreds of possible devices, handling the challenge of massively different measurement readings from one device to another shall be tackled.

To reach this goal we suggest enhancing the normalisation process proposed by Galvan-Tejada et al.[14] described in equation (2) to better accommodate readings from several different devices. The raw magnetometer readings are first used to generate a vector described in equation (1):

$$|M| = \sqrt{M_x^{\ 2} + M_y^{\ 2} + M_z^{\ 2}} \quad (1)$$

Then the generated magnitude vector is normalised as described in equation (2):

$$\forall i \in M : z_{i,d} = \frac{r_{i,d} - \mu_d}{\sigma_d} \quad (2)$$

Where M is the magnitude vector, M_x, M_y and M_z are the magnitude readings for the x, y and z axis of the magnetometer, $z_{i,d}$ is the normalised magnitude, $r_{i,d}$ refers to the i^{th} observation of the signature in dimension d, μ_d is the mean value of the signature for dimension d and σ_d is the standard deviation of the signature for dimension d. This method works well in all cases where the hardware is fixed and continuous readings provide more details. However, when using several different devices, the readings from one device to another tend to be way too different in real life. To demonstrate this some basic statistical descriptive data of 1500 magnetometer measurements is given from all 5 devices in point A of the data collecting test area.

As the data reveals, the average readings differ far too much not to require individual training of each specific device in an indoor positioning system.

The first strategy to enhance the measured data is to first do normalisation on the raw measurement data and then generate the magnitude vector for each reading.

$$\forall i \in M : q_{i,d} = \frac{s_{i,d} - \mu_d}{\sigma_d} \tag{3}$$

Where $q_{i,d}$ is the normalised reading, $s_{i,d}$ refers to the i^{th} observation of the measurement in dimension d, μ_d is the mean value of the measurement for dimension d and σ_d is the standard deviation of the measurement for dimension d.

$$|N| = \sqrt{N_x^{\ 2} + N_y^{\ 2} + N_z^{\ 2}} \tag{4}$$

Where N is the normalised magnitude vector, N_x, N_y and N_z are the normalised magnitude readings for the x, y and z axis of the magnetometer.

3. Results

We examined the measurement results from the standpoint of what dispersion they show. In the aspect of our study it is interesting since we used devices from the same manufacturer and running the same operation system. Therefore it would be evident for devices equipped with the same sensor to provide dispersions with no difference. After we processed the date, it turned out it is not our case. On the next figure the deviation we measured with the two HTC devices is seen.

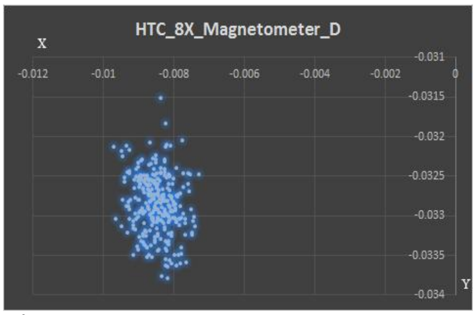

Fig. 4: Corner 'D' by HTC 8X

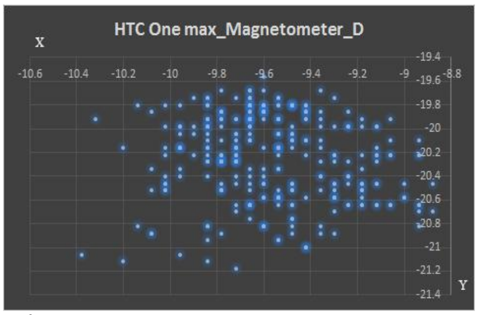

Fig. 5: Corner 'D' by HTC One Max

We got similar results with devices using the same operation system. We can see this on the following figures.

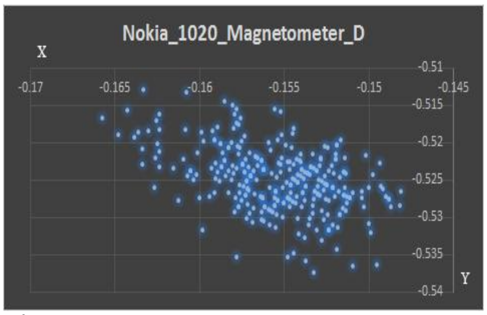

Fig. 6: Corner 'D' by WP

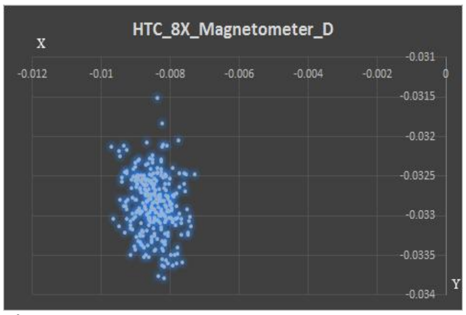

Fig. 7: Corner 'D' by WP

With the help of the several measurement results we attempted to replicate the floor maps of the test areas, but because of the many distractions unfortunately we didn't get useful results. This can be seen in the following figure.

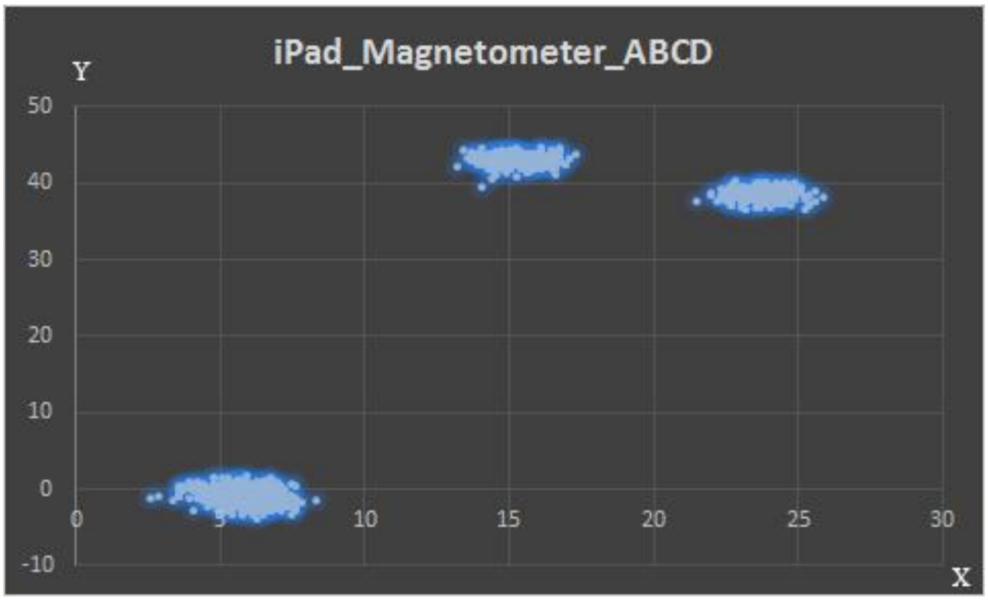

Fig. 8: The effect of interference on the measurement results of iPad mini

As the graph shows above, the sensor of iPad mini is so sensitive and works with so large error that is can't make a difference between corner 'C' and 'D' – though in reality they were 540 cm away from each other –, and made them one point.

We experienced similar result in the case of NOKIA 1020 device. Here the error was caused by the interference, which comes from the refrigerator in corner 'D'. After the equipment was turned off, we could sense all four corners. This can be seen on the next figure.

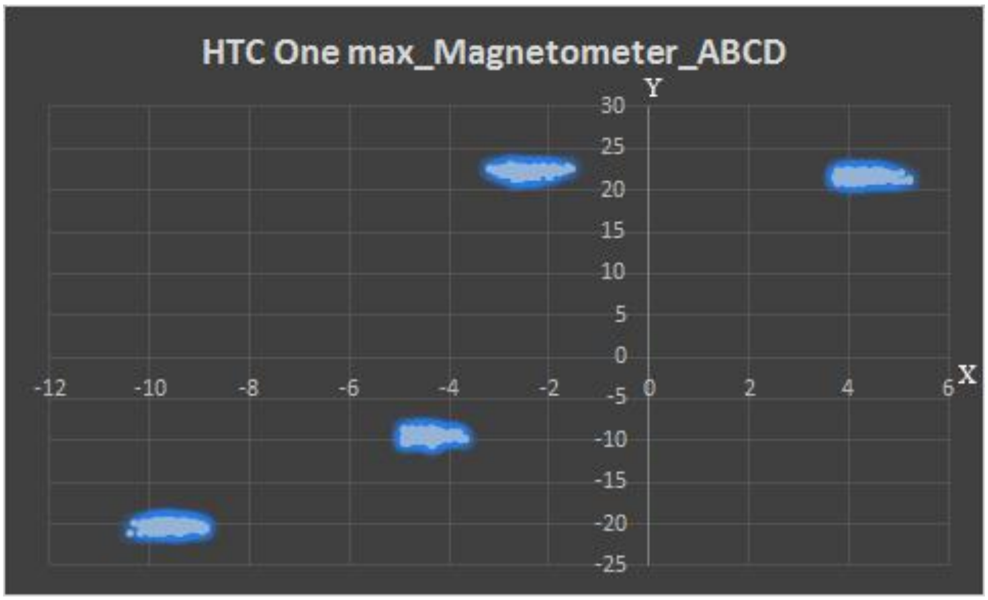

Fig. 9: The measurement results of HTC One Max after eliminating the interference

4. Conclusion

From the results described above it turns out that the operation of sensors is greatly influenced by the operating system running on the device. In addition we have to take numerous other factors causing measurement error in consideration. In many cases distortion attributable to interference exceeded 24%, which is considered to be a very high value in the case of indoor positioning. Interference also can be induced by cables running in the wall, which would cumulatively disturb the measurement result when in a large supermarket. Filtering it can be solved only by complex, elaborate algorithms, but then the load of available resources would grow again.

Due to the sensitivity of sensors we cannot estimate the sizes of the test area at the moment, and the accuracy of positioning is yet to reach the desired level.

5. Acknowledgement

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References

1. Ferenc Brachmann: A Multi-Platform Software Framework for the Analysis of Multiple Sensor Techniques in Hybrid Positioning Systems
2. Galvan-Tejada, C. E., Garcia-Vazquez, J. P., & Brena, R. (2013, November). Magnetic-Field Feature Reduction for Indoor Location Estimation Applying Multivariate Models. In Artificial Intelligence (MICAI), 2013 12th Mexican International Conference on (pp. 128-132). IEEE.
3. Karl Pearson (June 20, 1895) "Notes on regression and inheritance in the case of two parents," Proceedings of the Royal Society of London, 58: 240–242.
4. Mobile phone sensors: http://baike.baidu.com/view/9077573.htm
5. Zoltan Horvath, Andrea Baranyi: The Problematics of Indoor Navigation, 10th International Miklos Ivanyi phd & dla symposium abstract book, pp. 53., ISBN 978-963-7298-56-1
6. Zoltan Horvath, Hanna Horvath, “The Measurement Preciseness of the GPS Built in Smartphones and Tablets”, INTERNATIONAL JOURNAL ON ELECTRONICS AND COMMUNICATION TECHNOLOGY 1 :(5) pp. 17-19. (2014))