The Fusion of Smartphone Sensors for Indoor 3D Position and Orientation Estimation

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***Abstract*-The improvement in smartphone technology has encouraged the exploration in field of user experience. The internal inertial navigation system sensors of a smartphone enables it to infer the its three dimensional indoor orientation and position when it is being pointed at certain objects by hand. However, the sensors' flawed measurements complicate estimation of position and orientation precisely. Previous studies shows that sensor fusion of both internal and external measurements can enhanced the performance. However, those estimations didn't cover the pointer-like usage. To achieve the possibility of smartphone as pointer, the estimation using sensor fusion has been performed. Unfortunately, these experiments resulted in bad position estimation for small precision, while the orientation estimation was passable.**

***Index Terms*-Context-aware systems, Indoor localization, Wi-Fi fingerprinting, data fusion.**

INTRODUCTION

During cultural or tourism visits, an informative guide of the interesting objects is necessary to enhance the knowledge and the experience of the visitors. This guide, in the meantime, can be provided by the smartphone because of its capability of being context-aware system. Mostly, the smartphone uses the context of position in two dimension (2D). However, smartphone can explore more possibilities in indoor positioning using its sensors.

The captured context of smartphone sensors are composed in 3 dimensions (3D) of both position and orientation (in X, Y, and Z axes). Those dimensions can be used to explore the feasibility of smartphone as guide which is held by hand to point at interesting objects, which can't be handled by 2D position only. Thus, the user experience can be enhanced.

Nonetheless, the sensors of the smartphone are not perfect to acquire good estimations of position and orientation. Position estimation used erroneous double integration of the accelerometer, which has terrible noisy measurement, while orientation estimation is affected by the gyroscope's drift and the easily disturbed magnetometer [1]. Thus, those sensors cannot be used independently to give adequate information to estimate position and orientation.

To overcome these drawbacks, previous researches had investigated fusion of the smartphone sensors internally [2] and its surroundings, including Wi-Fi signal strength [3, 4]. These methods of sensor fusion had provided fine estimation in indoor environment.

Still, the 3D position and orientation were separately studied, while the closest approach was the heading (Z-axis) and position estimation. The other orientation elements are important to determine the precision in pointing a direction of a hidden or interesting object.

Yet, the 3D position and orientation had been studied using robot camera [5]. But, the usage of camera in smartphone is not applicable in this study as the camera will block user's vision and drain the smartphone battery.

This study presents of the Wi-Fi fingerprinting [3] and the smartphone sensors real-time data fusion to estimate the 3D position and orientation of smartphone held by hand. To provide the data fusion, Kalman Filter [6] and Complementary Filter [2] are used. These algorithms are implemented inside the smartphone to guarantee its mobile characteristic. Then, the feasibility of using smartphone as pointer will be discussed in the later section.

PROPOSED METHOD

This study involves the estimation of 3D orientation and position estimation as depicted in **Figure 1**. The 3D orientation estimation approach sensor fusion uses complementary filter [2] towards gyroscope angular velocity and combination of magnetic field from magnetometer and gravity acceleration from accelerometer (digital compass) real-time data. Then, the 3D position is estimated using the result of Kalman Filter towards Wi-Fi fingerprinting [3] result and the linear acceleration which is derived from the smartphone API (Application Programming Interface).

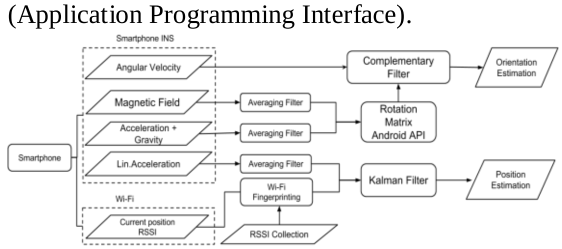

Figure 1. The proposed method flowchart.

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I. Complementary Filter

The complementary filter has an advantage to combine and smoothen the low-noise measurements by high pass filter, and high-noise measurements by the low pass filter [2]. This filter suits the characteristic of the gyroscope sensor for the high pass filter and the digital compass sensor for the low pass filter. Thus, these two measurements can be combined to have enhanced orientation estimation.

II. Wi-Fi fingerprinting

Wi-Fi fingerprinting by smartphone is based on two phases [3]. The offline phase acquires the radio signal strength indication (RSSI) from several reference points in desired environment and map them into the database of signal strength. Then, the online phase determines the position of user by comparing the current position RSSI with the RSSI map of signal strength from the offline phase. This position is obtained by weighted k-Nearest Neighbor [7], a deterministic positioning algorithm.

III. Kalman Filter

The Kalman Filter is widely used in data fusion because its popularity to minimize noises [4]. This filter recursively solves linear problem assuming the noise follows the Gaussian distribution using the previous time step state and the current measurement. The Kalman Filter is consisted of two stages: prediction (estimates the current state) and update (correcting the state using available observation).

In this case, the Kalman Filter's state are smartphone's position, velocity, and acceleration. Then, the available measurements for this filter are acceleration from linear acceleration and position from Wi-Fi fingerprinting.

Result and Discussion

The proposed method was tested using two scenarios of experiment. To test the quality of orientation estimation, a slow and a quick 90° rotation over all axis were performed. Then, position estimation quality was measured using 15 cm back-and-forth movement over all axis. The position estimation experiment was executed in two cases: within and without sensor fusion.

The orientation estimation has achieved a passable performance. This resulted in 32,406° standard deviation for Z-axis, 9,821° absolute error for X-axis, and 4,640° absolute error for Y-axis. Those errors were not mainly produced by the noisy sensors because some disturbance of hand from holding the smartphone might happen. The huge error in Z-axis case was also happened because of several electronic devices that might disturb the magnetometer.

However, the position orientation didn't work out by either fusion sensor or only accelerometer. Regardless of having 15 cm displacement each time, the estimation using accelerometer only gave accumulated error leading up to several meters displacement only in few seconds. In the other hand, Wi-Fi fingerprinting result and accelerometer fusion gave stagnant measurement of very far position (1 meter away) with small fluctuation around 2-3 cm.

Thus, by the incomplete position estimation result, the smartphone cannot serve pointer at all. However, it is possible to use another measurement to improve its quality.

Conclusion

According to the experimental result, the smartphone 3D position and orientation estimation using sensor fusion was not fully applicable. The estimation of position didn't work out well. However, the orientation estimation gave a promising result. In the future, the position estimation might be improved using another measurement, such as image processing by camera. Thus, the role of smartphone as pointer might be practicable afterwards.

References

[1] U. Shala and A. Rodriguez, "Indoor Positioning System using Sensor-fusion in Android Devices," Kristianstad University, Kristianstad, 2011.

[2] S. Ayub, A. Bahraminisaa and H. Bahram, "A sensor fusion method for smart phone orientation estimation," in *Proceedings of the 13th Annual Post Graduate Symposium on the Convergence of Telecommunications, Networking, and Broadcasting*, Liverpool, 2012.

[3] O. Costilla-Reyes and K. Namuduri, "Dynamic Wi-Fi Fingerprinting Indoor Positioning System," in *2014 International Conference on Indoor Positioning and Indoor Navigation*, 2014.

[4] Z. Chen, H. Zou, H. Jiang, Q. Zhu, Y. C. Soh and L. Xie, "Fusion of WiFi, Smartphone Sensors and Landmarks Using the Kalman Filter for Indoor Localization," *Sensors*, vol. 15, no. 6, pp. 715-732, 2015.

[5] J. Wang and W. J. Wilson, "3D Relative Position And Orientation Estimation Using Kalman Filter For Robot Control," in *IEEE International Conference on Robotics and Automation*, Nice, 1992.

[6] G. Welch and G. Bishop, An Introduction to the Kalman Filter, Chapel Hill: ACM, Inc., 2001.

[7] B. Li, J. Salter, A. G. Dempster and C. Rizos, "indoor positioning techniques based on wireless LAN," in *LAN, First IEEE International Conference on Wireless Broadband and Ultra Wideband Communications*, 2007.