Preliminary study for improving accuracy on Indoor positioning method using compass and walking detect

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Abstract. Indoor positioning technology is commercially available now, however, the positioning accuracy is not sufficient in the current technologies. Currently available indoor positioning technologies differ in terms of accuracy, costs and effort, but have improved quickly in the last couple of years. It has been actively conducted research for estimating indoor location using RSSI (Received Signal Strength Indicator) level of Wi-Fi access points or BLE (Bluetooth Low Energy) tags. WiFi signal is commonly used for the indoor positioning technology. However, It requires an external power source, more setup costs and expensive. BLE is inexpensive, small, have a long battery life and do not require an external energy source. Therefore, using BLE tags we might be able to make the positioning system practical and inexpensive way. In this paper, we investigate such practical type of indoor positioning method based on BLE. BLE RSSI are processed by Multilayer Perceptron(MLP). Also, compass data and walking speed estimation with an extended Kalman filter is used to improve the accuracy. Our preliminary experimental result shows 2.21m error in case of the MLP output. In preliminary experimental results, the proposed approach improved the accuracy of indoor positioning by 21.2%.

Keywords: indoor positioning, BLE, fingerprint, Extended Kalman filter

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1 Introduction

In case of outdoor positioning, satellite-based GPS positioning works very well. However, indoor positioning is not so straight forward, and that area is glowing research fields in mobile computing because of the popularization of mobile devices, like smartphones, tablets. The technologies currently used most in the development of Real-Time Location System are, RFID (Radio Frequency IDentification), Wi-Fi or BLE (Bluetooth Low Energy)[1][2][3][4]. Indoor positioning technology is commercially available now, however, the positioning accuracy is not sufficient in current technologies. Currently available indoor positioning technologies differ in terms of accuracy, costs and effort, but have improved quickly in the last couple of years. WiFi signal is commonly used for the indoor positioning technology. However, WiFi equipment requires an external power source, more setup costs and expensive. Bluetooth Low Energy (BLE) is one of the latest technologies. It is called BLE beacons (or iBeacons) that are inexpensive, small, have a long battery life and do not require an external energy source. BLE technologies bring a couple of advantages: easy deployment and are integrated in most of the current electronic devices. Thus, it has been actively conducted research for estimating indoor location using RSSI (Received Signal Strength Indicator) level of BLE tags. There are also some indoor localization studies using accelerometer and geomagnetic sensor. Most modern smartphones are equipped with those sensors. Those studies estimated both position and direction of the target object and also detected walking, but their positioning accuracy was insufficient. Kumar[5] reported localization using the RSSI values of the anchor node beacons and the multi-layer perceptron (MLP)-based classifier. Zhang[6] utilized smartphone sensors and Kalman filter for location estimation. Liu[7] also tried smartphone sensors and particle filters to improve the location estimation. In this paper, we report a preliminary study of position estimation using ibeacon RSSI and smartphone sensors (inertial and geomagnetic) combined with Extended Kalman Filter-based estimation. In terms of the calculation cost and extension to non-linear system, in this study, extended Kalman filter has been investigated for the estimation of the indoor location.

2 Proposed Method

Figure 1 shows the basic building block of the proposed positioning system. The inputs are the location information of BLE tags and RSSI. The MLP estimates the location where $\boldsymbol{x}$ and $\boldsymbol{y}$ are the expected location coordinates. The advantages of using BLE tags are not only improving the cost performance, but we might be able to implement many applications associated with BLE tags. Using the smartphone, the acceleration information and the geomagnetic information are obtained and converted into the velocity and the rotational velocity values, respectively. Then the extended Kalman filter estimates the location (X, Y) using the inputs $(\boldsymbol{x}, \boldsymbol{y})$, velocity, and rotational velocity.

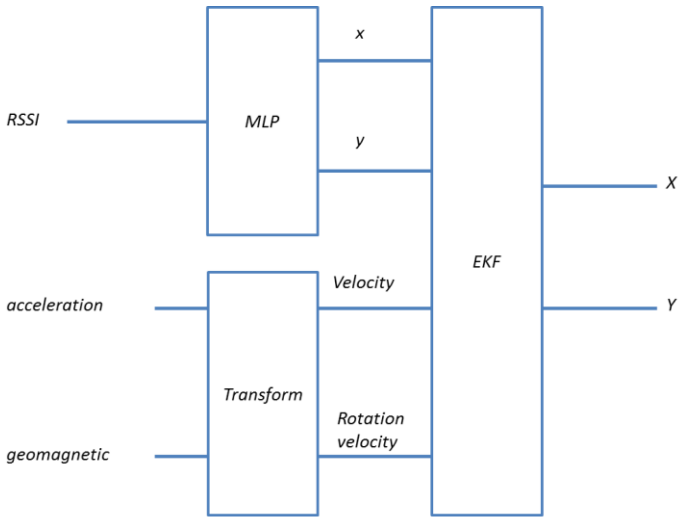

Figure 1. Block diagram of the proposed system

3 Location Estimation using MLP with Fingerprints

The estimation accuracy of the MLP output was evaluated. First, the training data of fingerprints were collected using the smartphone. The experimental environment is shown in Figure 2. Four BLE beacons were symmetrically arranged along the periphery of the (4 × 4)-m2 square zone. RSSI values were measured 20 times at each 16 blocks as shown in Figure 2. For the evaluation, we took the dotted route in Figure 2, and measured RSSI values from the four BLEs every 1sec. The location was then estimated by the MLP algorithm. The experimental result showed that the maximum error, the minimum error and the average error were 3.61m, 1.00m, 2.21m, respectively. Figure 3 shows the measured RSSI values.

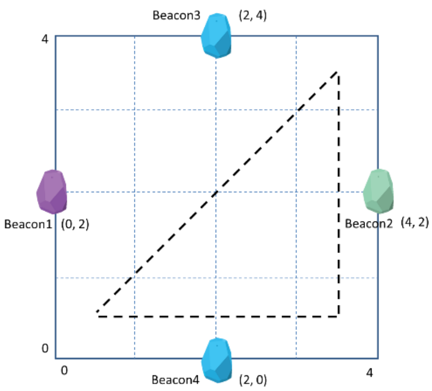

Figure 2. Experimental environment

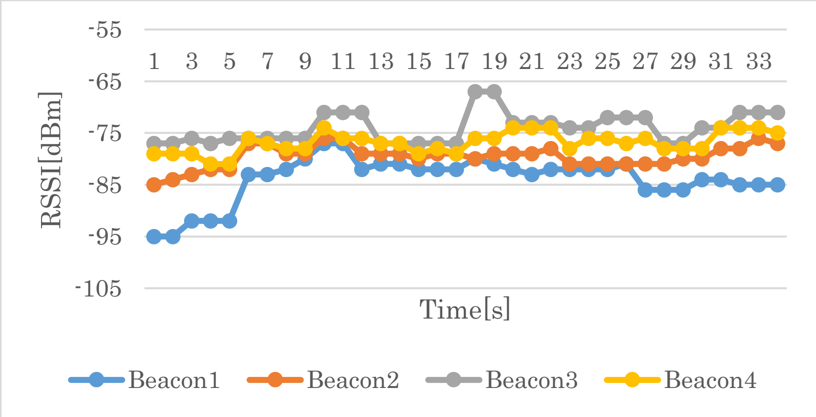

Figure 3. Observed RSSI values

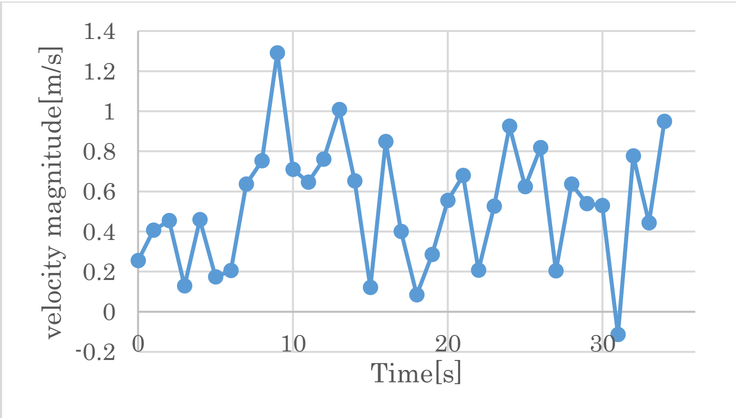

Figure 4. Observed velocity values

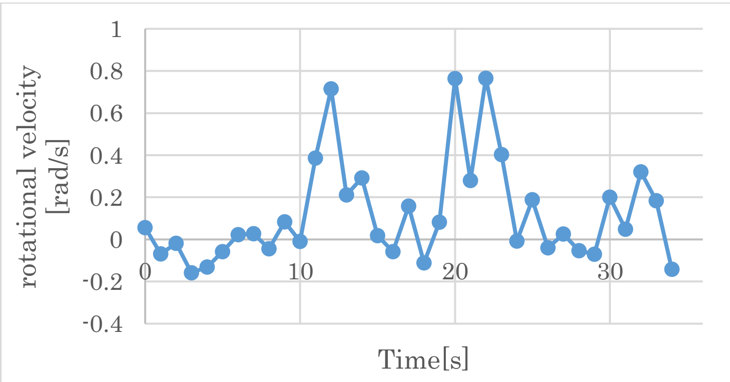

Figure 5. Observed rotation velocity values

Our simple and small area localization test using MLP and fingerprint aims to understand the basic performance using BLE tags. The result was not stable enough, however, we will use the estimation result as the reference to the proposed method.

4 Evaluation of the Proposed Method

Figure4 and Figure5 are the velocity and the rotation velocity respectively. Those values were measured using smartphone together with the RSSI values as shown in Figure3. In our proposed method, using extended Kalman filter, the discrete-time state transition model is as follows;

$$\boldsymbol{x}(k) = \boldsymbol{f}\big(\boldsymbol{x}(k-1), \theta(k-1), v(k-1)\big) + \boldsymbol{e_1}(k-1)$$

$$\boldsymbol{f}(\boldsymbol{x}\,(k-1), \theta(k-1), v(k-1)) = \begin{bmatrix} x(k-1) + Tv(k-1)\cos\theta(k-1) \\ y(k-1) + Tv(k-1)\sin\theta(k-1) \\ \theta(k-1) + T\omega(k-1) \\ v(k-1) \end{bmatrix}$$

where location coordinates (x, y), velocity v, attitude angle θ, rotational velocity ω, sampling period T were used. $\boldsymbol{e}_1(k)$ is the process noise which is assumed to be zero mean multivariate Gaussian noise with covariance Q. Also, the observation equation is as follows;

$$\boldsymbol{y}(k) = \begin{bmatrix} x_e(k) \\ y_e(k) \end{bmatrix} = \boldsymbol{h}(x(k)) + \boldsymbol{e_2}(k)$$

where the coordinates $(x_e(k), y_e(k))$ is obtained from the MLP outputs, $\boldsymbol{h}(\boldsymbol{x}(k))$ is a function representing the observation, $\boldsymbol{e}_2$ is the noise input to the observation and follows the covariance matrix R.

As shown below, Step1 and Step2 are the prediction and filtering steps of the extended Kalman filter, respectively. From the above state equation and observation equation, the extended Kalman filter is calculated by the following two-step recursive processing.

Step1

$$\hat{\boldsymbol{x}}^{-}(k) = \boldsymbol{f}(\hat{\boldsymbol{x}}(k-1), \theta(k-1), v(k-1))$$

$$\boldsymbol{P}^{-}(k) = \boldsymbol{F}(k)\boldsymbol{P}(k-1)\boldsymbol{F}^{\boldsymbol{T}}(k) + Q$$

Step2

$$\boldsymbol{g}(k) = \frac{\boldsymbol{P}^{-}(k)\boldsymbol{H}(k)}{\boldsymbol{H}^{\boldsymbol{T}}(k)\boldsymbol{P}^{-}(k)\boldsymbol{H}(k) + R}$$

$$\widehat{\boldsymbol{x}}(k) = \widehat{\boldsymbol{x}}^{-}(k) + \boldsymbol{g}(k)\{\boldsymbol{y}(k) - \boldsymbol{h}(\widehat{\boldsymbol{x}}^{-}(k))\}$$

$$\boldsymbol{P}(k) = \{\boldsymbol{I} - \boldsymbol{g}(k)\boldsymbol{H}^{T}(k)\}\boldsymbol{P}^{-}(k)$$

$$\boldsymbol{F}(k) = \frac{\partial \boldsymbol{f}(\boldsymbol{x}(k), \theta(k), v(k))}{\partial \boldsymbol{x}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ -Tv(\mathrm{k})\sin\theta(k) & Tv(\mathrm{k})\cos\theta(k) & 1 & 0 \\ T\cos\theta(k) & T\sin\theta(k) & 0 & 1 \end{bmatrix}$$

where the ***H(k)*** is a 4 × 4 identity matrix, $\widehat{\boldsymbol{x}}^{-}$ is the prestate estimate, $\widehat{\boldsymbol{x}}$ is the state estimate, $\boldsymbol{P}^{-}$ is the previous error covariance matrix, $\boldsymbol{P}$ is the posteriori error covariance matrix, and $\boldsymbol{g}$ is the Kalman gain. By calculating these values, the estimated value can be obtained.

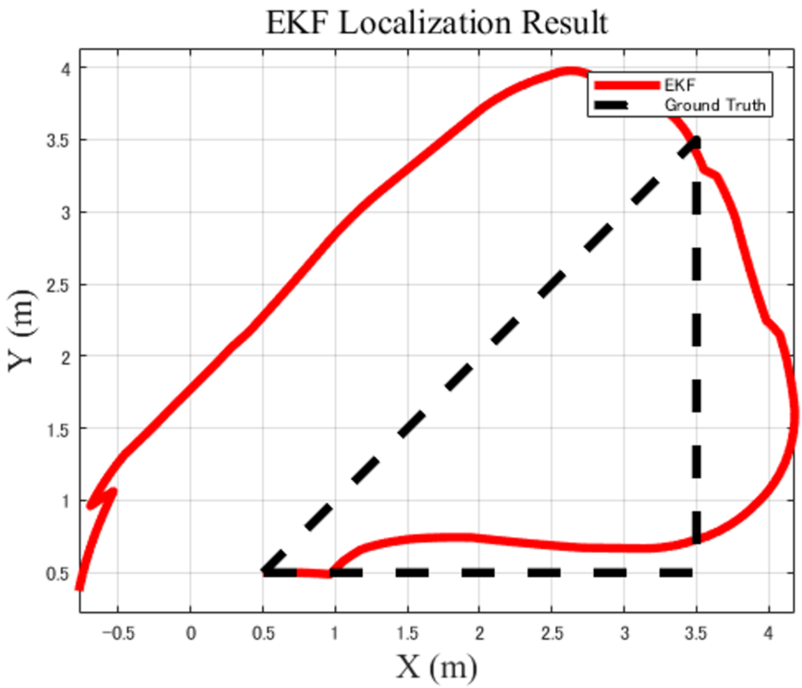

Figure 6. The actual walking path (dotted line) and the estimated result (red line)

5 Experimental Results

The experimental result showed that the maximum error, the minimum error, and the average error were 2.92m, 0.51m, and 1.75m. This experiment was measured thirty-four times in every one second. The average error, minimum error and maximum error were 21.2%, 49.0% and 19.1% lower compare with the result from the experiment using just MLP.

6 Discussion

The error is considerably smaller in case of the proposed method than the method using just MLP. However, the accuracy remains insufficient, and need to be carefully investigated. Also, the accuracy is depending on the experimental environment. Therefore, we need to consider the factors which make RSSI unstable. We will also investigate other estimation methods, which were not carefully considered in the present study.

7 Conclusion

The accuracy improvement of an indoor positioning method using a compass and walking detection was assessed in a preliminary study. MLP, linear velocity, and rotational velocity were combined and tested in an extended Kalman filter. We compared the overall fingerprint-matching performance between the proposed method and a conventional method. The accuracy was improved in the proposed method (by over 20%), but the improvement was insufficient.

8 Reference

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