Integrated Wi-Fi Fingerprinting and Inertial Sensing for Indoor Positioning

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***Abstract*—Indoor positioning has emerged as a widely used application of Wi-Fi wireless networks. A region-based fingerprinting approach is presented for indoor positioning in Wi-Fi wireless networks. This proposed method compares the fingerprint of a Wi-Fi tag with that of a region-based group of reference points, instead of an individual reference point. With the fingerprinting position estimate obtained, and with an inertial measurement unit integrated with the Wi-Fi tag, a stochastic system model is adopted to track the target's position when it is in piecewise constant velocity motion in Wi-Fi wireless networks. The stochastic system model utilizes Wi-Fi fingerprinting position estimates as measurements and inertial sensing data as control inputs. Both simulation studies and experiment data have shown the positioning performance of the integrated mobile platform with improved accuracy, by using the proposed Wi-Fi and inertial sensing technologies.**

***Keywords* — Indoor positioning; Wi-Fi fingerprinting; Region-based; Inertial measurement**

I. Introduction

Wi-Fi wireless networks provide the next generation wireless communication technology and have been used for various applications, including indoor positioning [1]. Together with UWB and ZigBee, Wi-Fi is among the three main indoor positioning technologies available on the markets. Compared with UWB, WiFi network is accessible to any user with a ultra mobile PC or a smart mobile phone. Another advantage of WiFi is that due to its popular usages, the cost of implementing its infrastructure has drastically dropped to a level much lower than that of UWB. Compared with ZigBee, WiFi radio transmission is less susceptible to blockage by pillars or walls within the indoor environment, whilst the cost of a WiFi tag is nearly the same as that of a ZigBee tag. Although WiFi tag's higher power consumption gives the impression that the battery life span is far less than its ZigBee counterpart, its transmission rate is much higher and it takes shorter time to transmit the same radio packet, thus the energy needed to transmit is comparable to ZigBee.

The objective of this paper is to provide solutions to perform real-time indoor positioning with Wi-Fi technology as well as inertial sensing. The rest of the paper is organized as follows. Section II introduces a novel region-based fingerprinting indoor positioning approach for Wi-Fi networks. Section III presents the fusion of Wi-Fi data with additional inertial sensing data to improve positioning accuracy. Section IV concludes the paper with a brief discussion on our future research agenda.

II. Region-based Fingerprinting

The fingerprinting technique has been introduced in [2] as an effective approach for indoor positioning. It utilizes received signal strength (RSS) measurements in Wi-Fi wireless networks, and a typical fingerprinting indoor positioning system usually consists of (i) n Wi-Fi access points, (ii) m reference points and (iii) u Wi-Fi tags as tracking objects. In such a system, Euclidean distance in signal strength is used to evaluate the geographical relation between a Wi-Fi tag and a reference point. Euclidean distance in signal strength between the Wi-Fi tag and the reference point j is defined as

$$E_j = \sqrt{\sum_{i=1}^{n} (\theta_{ji} - S_i)^2} \ , \tag{1}$$

where E_j denotes the 'dissimilarity' in signal strength space between the reference point j and the Wi-Fi tag, the signal strength vector $\vec{S} = (S_1, S_2, \ldots, S_n)$ denotes a Wi-Fi tag's signal strengths perceived on the n access points, and the signal strength vector $\vec{\theta}_j = (\theta_{j1}, \theta_{j2}, \ldots, \theta_{jn})$ denotes the signal strengths the j^{th} reference point receives from the n access points [3]. Intuitively, the nearer the reference point j is to the Wi-Fi tag, the smaller E_j is.

In a 2D sensing network, we use the coordinates of a few neighboring reference points to localize a Wi-Fi tag, and we do not need to know the access points' positions. The Wi-Fi tag's coordinates $\mathbf{x}_0 = (x_0, y_0)$ is determined as a linear combination of the neighboring reference points' coordinates $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m)$, where $\mathbf{x}_j = (x_j, y_j)$, $j \in (1, m)$ represents the j^{th} reference point's coordinates. In signal strength space, we select m nearest neighboring reference points by choosing m smallest E_j. The unknown Wi-Fi tag's coordinates $\mathbf{x}_0 = (x_0, y_0)$ is estimated as

$$\hat{\mathbf{x}}_0 = \sum_{j=1}^{m} w_j \mathbf{x}_j \ , \tag{2}$$

where w_j is the weighting factor to the j^{th} neighboring reference point.

The k-nearest-neighbor approach introduced in [4] assumes that the j^{th} neighboring reference point's weighting factor $w_j = 1/j$, i.e., the same weight is assigned to each of the k nearest neighbors. In contrast, the weighted k-nearest-neighbor approach introduced in [3] uses E_j to define w_j:

$$w_j = \frac{1}{E_j^2} \Bigg/ \sum_{j=1}^{m} \frac{1}{E_j^2} \tag{3}$$

As discussed earlier, the weighted k-nearest-neighbor method is based on the assumption that if the reference point j is near to the Wi-Fi tag, then the Euclidean distance in signal strength E_j between them is small, and vice versa. In practice, however, this assumption fails to hold in many occasions, due to fluctuations in RSS measurements. Outlier RSS measurements will consequently deteriorate the localization accuracy, if we implement the deterministic k-nearest-neighbor method.

To solve this problem, we develop a region-based fingerprinting localization approach. We form N reference points (N could be 4, 6, etc.) into a group, and each group of reference points covers a region in our Wi-Fi indoor positioning test-bed. From the viewpoint of fingerprinting mechanism, each fingerprint is a region-based group of reference points in our approach, instead of an individual reference point. To determine which fingerprint best matches the Wi-Fi tag's RSS measurements, we calculate the sum of Euclidean distance (SED) in signal space, and the region with the minimum SED will be selected as the matched region (see Figure 1).

In our test-bed we group reference points to form convex regions for positioning purpose. The key advantage of our proposed approach is that high positioning accuracy can be achieved. The drawback is that the required system calibration is more laborious due to the grouping effort, which is case-by-case depending on the environment.

We evaluate the performance of region-based fingerprinting algorithm using simulation studies. We assume each access point's communication radius is sufficient to cover the whole area of the network. The simulation setup is as follows. In a 20×20 meter^2 wireless network with 4 access points at the edge of the square, we generate the RSS at 20 reference points using the propagation model with a Gaussian noise, and store the measurements into the calibration database. We move the Wi-Fi tag along a track in unit step, and calculate its position estimate at the end of each step using (i) individual fingerprinting and (ii) region-based fingerprinting by grouping 4 reference points in 9 squares of 2×2 meter^2 2a. The performance metric of our simulation study is defined as the position estimate's normalized error, i.e.,

$$\frac{1}{N} \sum_{i=1}^{N} \sqrt{\left(\mathbf{x}_{i,0} - \hat{\mathbf{x}}_{i,0}\right)^T \left(\mathbf{x}_{i,0} - \hat{\mathbf{x}}_{i,0}\right)}$$

where N is the number of estimates throughout the indoor positioning process, and $\hat{\mathbf{x}}_{i,0}$ represents the estimate of the Wi-Fi tag's true position $\mathbf{x}_{i,0}$ at the i^{th} step. By applying the region-based approach in our indoor positioning system, we improve the positioning accuracy by 1.5 meters in average in our test-bed, as shown in Figure 2.

III. Integrated Wi-Fi Fingerprinting and Inertial Sensing

For indoor positioning in our Wi-Fi wireless network, we have established an integrated mobile platform featuring both Wi-Fi and inertial sensing. We select the low-cost G2 microsystem as our Wi-Fi tag. It supports IEEE 802.11 b/g Wi-Fi standards, and provides a PCB for integration with additional sensors. We integrate the Wi-Fi tag with a RAZOR inertial measurement unit (IMU). The RAZOR IMU consists of a single-axis gyroscope (LY530AL) plus a dual-axis gyroscope (LPR530AL), a triple-axis accelerometer (ADXL345), and a triple-axis magnetometer (HMC5843). It operates at 10Hz and provides 9 degrees of inertial measurements.

A. Inertial Data Processing

The objective of inertial data processing is to determine the orientation and acceleration of the integrated mobile platform. We mount the mobile platform on a trolley for indoor positioning experiments in our Wi-Fi wireless network. For discussion convenience, we define a local x-y-z frame of the mobile platform, as well as a reference coordinate frame of the horizon/ground where the X-axis points east, Y-axis points north, and Z-axis points up. The orientation and acceleration of the mobile platform are determined relative to the reference frame.

The orientation of the mobile platform is described by the following three angles: (i) elevation, (ii) bank and (iii) heading. The elevation angle θ and the bank angle ϕ are respectively

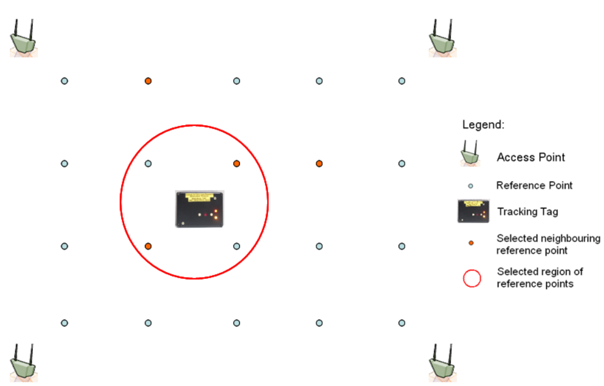
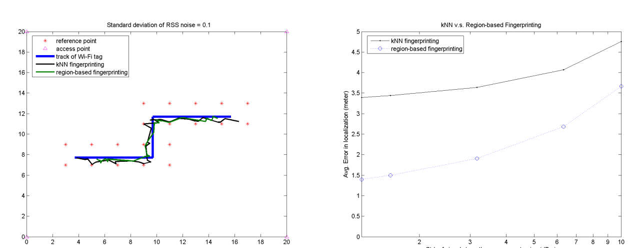


Fig. 1. Region-based fingerprinting algorithm.



(a) (b)

Fig. 2. Wi-Fi tag tracking and its positioning error using individual/region-based fingerprinting algorithm.

defined as the angle rotated about the y-axis and x-axis with respect to the horizon/ground.

$$\theta = \arcsin \frac{\ddot{x}'}{\sqrt{(\ddot{x}')^2 + (\ddot{y}')^2 + (\ddot{z}')^2}}$$

$$\phi = \arcsin \frac{\ddot{y}'}{\sqrt{(\ddot{x}')^2 + (\ddot{y}')^2 + (\ddot{z}')^2}}$$

where $\ddot{x}'$, $\ddot{y}'$ and $\ddot{z}'$ are the accelerometer readings, i.e., the accelerations along the x, y and z-axis in the local frame.

The heading angle ψ is defined as the angle rotated about the z-axis with respect to the horizon/ground. To determine ψ, we should not use accelerations, because gravity is irrelevant to z-axis rotations, and cannot be used to calculate the heading angle. Instead, we may use either the magnetometer's reading along the x and y-axis or the gyroscope's angular velocity measurement about the z-axis. To use magnetic data, we need to firstly realign the local frame's z-axis with the Z-axis (the gravitational axis) in the reference frame, because sensitivity of magnetic data decreases as elevation and bank angles increase. The realignment can be implemented by the following rotation matrix:

$$\mathbf{R}' = \mathbf{R}_\phi^x \mathbf{R}_\theta^y$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & \sin\phi \\ 0 & -\sin\phi & \cos\phi \end{bmatrix} \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix}$$

In our scenario, assuming that the local frame's x-y plane and the reference frame's X-Y plane are coplanar (the trolley's top surface is parallel with the ground), $\theta = \phi = 0$, and hence the rotation matrix $\mathbf{R}' = \mathbf{I_{3\times3}}$. Therefore, the magnetic data in the local frame is identical to that in the reference frame, and the magnetometer-determined heading can be calculated accordingly:

$$h_{mag} = \arctan\left(\frac{m_y}{m_x}\right)$$

where m_x and m_y are the Earth magnetic field's components along the x and y-axis of the local frame.

Alternatively, we can determine the heading by integrating the z-axis angular velocity measurement of the gyroscope:

$$h_k = h_{k-1} + \omega_k dt$$

where h_k is the gyroscope-determined heading and ω_k is the angular velocity at the k^{th} time step.

A complementary filter was proposed by Klingbeil and Wark to combine the advantage of magnetic and gyroscope data, so that the obtained heading reading is more stable in long term than that based on either of the above mentioned method alone [5]. With a fixed complementary weigh W, the heading angle is determined as follows.

$$\psi = (1-W)h_k + Wh_{mag} = (1-W)(h_{k-1}+\omega_k dt) + Wh_{mag}$$

Experimental results reported in [5] shows that the complementary filter helps improve the accuracy of the heading estimation.

We utilize the accelerometer readings as well as the orientation angles to determine the mobile platform's accelerations along the X and Y-axis in the reference frame, which will be useful for data fusion with Wi-Fi fingerprinting measurements. Coordinate transformation is implemented to convert the accelerometer readings, i.e., accelerations in the local frame to accelerations in the reference frame. As previously discussed, $\mathbf{R}' = \mathbf{I_{3\times3}}$ and coordinate transformation is not necessary in our scenario. Using the heading angle ψ, we can determine the rotation matrix about the Z-axis as follow.

$$\mathbf{R}_\psi^z = \begin{bmatrix} \cos\psi & \sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Subsequently,

$$\ddot{x} = \ddot{x}' \cos\psi - \ddot{y}' \sin\psi$$
$$\ddot{y} = \ddot{x}' \sin\psi + \ddot{y}' \cos\psi$$

where $\ddot{x}$ and $\ddot{y}$ are the accelerations of our concern along the X and Y-axis in the reference frame.

B. Kalman Filtering

Besides the fingerprinting approach described in Section II, a stochastic system model is needed for indoor mobile positioning, for the following two reasons. Firstly, the Wi-Fi tag, i.e., our tracking object is driven by control inputs and disturbances that we cannot model deterministically. Secondly, the Wi-Fi fingerprinting system does not provide perfect and complete information about the target.

We choose the Kalman Filter as our system model. We use the Kalman Filter to estimate the instantaneous state of a linear dynamic system, with measurements linearly related to the state but perturbed by white noise. The estimator uses incomplete and noise-corrupted measurements to estimate the tracking object's state, and the resulting estimation is statistically optimal with respect to any quadratic function of estimation error.

Assuming that we are tracking a single object in piecewise constant velocity motion in our Wi-Fi indoor positioning testbed, we describe our system dynamic model of the tracking object as follows:

$$\mathbf{x}_k = \mathbf{\Phi}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k, \tag{4}$$

where the state vector $\mathbf{x}_k$ includes the state variables of the x and y positions/velocities as well as the heading angle of the tracking object at the k^{th} time step,

$$\mathbf{x}_k = \begin{bmatrix} x_k & \dot{x}_k & y_k & \dot{y}_k \end{bmatrix}^T,$$

the control input $\mathbf{u}_k$ includes the x and y accelerations of the tracking object,

$$\mathbf{u}_k = \begin{bmatrix} \ddot{x}_k & \ddot{y}_k \end{bmatrix}^T,$$

the state transition matrix and the input coupling matrix are

$$\mathbf{\Phi}_k = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \text{ and } \mathbf{B}_k = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix}$$

and the process noise $\mathbf{w}_k$ is assumed to be a vector of independent, zero-mean Gaussian noises of the respective state variables. The covariance of $\mathbf{w}_k$ is $\mathbf{Q}_k$.

The measurement model is another requirement to build up the estimation scheme. The measurement model of the tracking object is as follows:

$$Z_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k$$

where the measurement sensitivity matrix is

$$\mathbf{H}_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

and the measurement noise $\mathbf{v}_k$ is assumed to be a vector of independent, zero-mean Gaussian noises of the respective variables in the measurement vector Z_k. The covariance of $\mathbf{v}_k$ is $\mathbf{R}_k$.

The prediction and update process of the Kalman Filtering is summarized in the following steps.

- Prediction:

$$\hat{\mathbf{x}}_k^- = \mathbf{\Phi}_k \hat{\mathbf{x}}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k$$

$$\mathbf{P}_k^- = \mathbf{\Phi}_k \mathbf{P}_{k-1} \mathbf{\Phi}_k^T + \mathbf{Q}_k$$

- Update:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1}$$

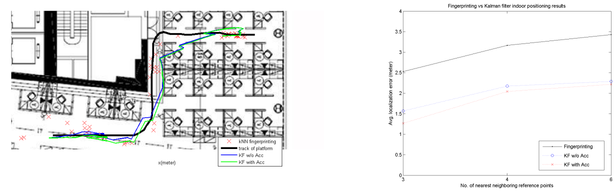
$$\mathbf{I}_k = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_k^-$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k \mathbf{I}_k$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}_k \mathbf{H}_k \mathbf{P}_k^-$$

where $\mathbf{K}_k$ is the Kalman Filtering gain, and the innovation $\mathbf{I}_k$ is the difference between the actual measurement and the predicted measurement at the k^{th} time step.

We use experimental data to verify the effectiveness of the integrated indoor positioning platform and the algorithm we adopt. The real-time indoor positioning experiment can be divided into two phases: calibration and tracking. In the test-bed in our lab, we measured the RSSs at 24 reference points in the calibration phase, measured integrated mobile platform's real-time Wi-Fi and inertial sensing information in the tracking phase, and transmitted both the measurements via Wi-Fi routers squares to a centralized database for processing. The indoor positioning experiment result is shown in Figure 3a, with the comparison among the three approaches: (i) kNN fingerprinting solely, (ii) kNN fingerprinting plus an incomplete Kalman Filtering model without control input in Equation 4, and (iii) kNN fingerprinting plus a complete Kalman Filtering model. We vary the number of neighboring reference points from 3 to 4 to 6. From the result shown in Figure 3b, we observe improvement of 1 meter in positioning accuracy in average by adding the incomplete Kalman Filtering model to kNN fingerprinting, and further improvement of 0.2 meters in positioning accuracy in average by adding control inputs to the Kalman Filtering model.



(a) (b)

Fig. 3. Wi-Fi and inertial sensing using Kalman Filtering.

IV. Conclusion

In this paper we have proposed a region-based fingerprinting method for indoor positioning in Wi-Fi wireless networks. We utilize a Wi-Fi tag to collect RSS information and localize the tag by comparing its RSS fingerprint with the RSS fingerprint of a region-based group of reference points. Based on the fingerprinting positioning results, and after integrating the Wi-Fi tag into a platform with inertial sensing capabilities, we introduce a Kalman Filtering model to track the platform's position when it is in piecewise constant velocity motion. Inertial sensing data provides control inputs in the Kalman Filtering model. Both simulation and experimental results have shown improved positioning accuracy by adopting our fingerprinting and data fusion method. Our future work may include investigation on how indoor positioning accuracy is influenced by multi-path signals, shadowing and other possible environmental changes in our Wi-Fi network. It may also include comparison of our approach with other available wireless network localization methods, such as Malguki Spring Model [6] and Maximum Likelihood Estimation [7].

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