

# Continuous Indoor Localization and Navigation Based on Low-cost INS/Wi-Fi Integration

Wennan Chai<sup>\*</sup>, Junchuan Zhou<sup>\*</sup>, Cheng Chen<sup>\*\*</sup>, Holger Nies<sup>\*</sup> and Otmar Loffeld<sup>\*</sup>

<sup>\*</sup> Center for Sensorsystems (ZESS), University of Siegen, Siegen, Germany, Email: {chai, zhou, nies, loffeld}@zess.uni-siegen.de

<sup>\*\*</sup> Institute of automatic control engineering (RST), University of Siegen, Siegen, Germany, Email: c.chen@zess.uni-siegen.de

**Abstract**—The widely diffused Wi-Fi infrastructure can be used for the indoor positioning and a lot of Wi-Fi localization techniques have been studied recently. However, for continuous indoor navigation of a mobile object, most of the existing methods do not give a satisfactory performance. The inertial measurement unit (IMU), providing the motion information of the object with a high update rate, is widely used in dead-reckoning navigation applications. By using the complementary nature of Inertial Navigation System (INS) and Wi-Fi positioning principles, an integrated system of INS and Wi-Fi is expected to form a low-cost, robust and continuous indoor navigation solution. In this paper, two loosely-coupled INS/Wi-Fi schemes and one tightly-coupled integration approach are presented.

**Keywords** — Wireless Local Area Networks; Inertial Navigation System; Fingerprinting; Unscented Kalman Filter

## I. INTRODUCTION

For outdoor positioning and navigation, solutions based on Global Navigation Satellite System (GNSS) are satisfactory in most applications. But such technology is not utilizable for most indoor applications. Lately, a number of positioning techniques have been developed for indoor environments (e.g., the methods based on Wireless Local Area Networks (WLAN), Bluetooth, Radio Frequency Identification (RFID), Ultra Wideband (UWB), infrared and ultrasound, etc). Among these techniques, the approach on the basis of exploiting 802.11 WLAN (Wi-Fi) is attractive, which is expected to yield a cost-effective and easy-accessible solution. Recently, the localization methodologies based on Wi-Fi rely on the Signal to Noise Ratio (SNR) or the received signal strength (RSS) [16].

Most of them, comprising the widely referred RADAR method, employ fingerprinting methods. In [3], two approaches are proposed to build the fingerprinting database, namely, the empirical method and the Wall Attenuation Factor (WAF) model based method. The first method always yields relatively better performance but requires significant implementation effort [3]. The positioning can also be achieved by directly employing field propagation models with weighted least squares, but the estimation accuracy normally shows large deviations.

The former mentioned approaches are not ideal for

some applications, such as the real-time continuous navigation, especially those related to mobile robot control. There are also other approaches presented using Wi-Fi continuous localization, such as Viterbi-like algorithms [4][17] and Baum-Welch algorithms [16]. However, they are mostly based on the “most likely” trajectory or path model which limits their robustness in practical applications. Moreover, they cannot provide satisfactory estimation results using total kinematic states on position, velocity and attitude estimates of a mobile object.

The Micro-Electromechanical Systems (MEMS) based inertial measurement unit (IMU) is widely used in navigation applications. The IMU provides the motion information of the object with a high update rate. Nevertheless, for a low-cost MEMS-based IMU, its navigation solutions drift quickly over time due to the accumulation of sensor errors (i.e., sensor bias, noise, scale factors, etc). In outdoor environments, the IMU is often used as a complementary sensor to a Global Positioning System (GPS) receiver. The INS/GPS integration has been proven to be a reliable solution for continuous outdoor navigation [5][7]. In [11], a Wi-Fi assisted dead-reckoning navigation system is proposed and the experimental results are encouraging.

The integration of INS/Wi-Fi system is expected to give continuous indoor localization and navigation solutions in case the inertial sensor is carefully calibrated. This paper concentrates on the INS/Wi-Fi integration approaches and three integrated systems are presented: the first one is the integration of INS with empirical fingerprinting positioning; the second one is the integration of INS with WAF model based fingerprinting positioning; the third one is the integration of INS and simplified propagation model.

## II. DESCRIPTIONS OF THE APPROACHES

### A. INS process model using Euler angles

The INS process model with Euler angles [12] is used as the system dynamic model in the INS/Wi-Fi integrated systems. For low-cost MEMS based IMUs, the effects from the earth rotation cannot be observed so that the Coriolis and centrifugal terms are not considered in the INS process model. The gravity is assumed as a constant and the transport rate is neglected. The simplified mechanization model can be expressed as Equation (1).

This model is widely used for low-cost IMUs [12] and it will be applied as the system process model for the predict step of the integration systems.

$$\begin{aligned} \mathbf{r}_k &= \mathbf{r}_{k-1} + \mathbf{v}_{k-1} \cdot \Delta t \\ \mathbf{v}_k &= \mathbf{v}_{k-1} + \left[ \mathbf{C}_{b,k-1}^n \cdot (\tilde{\mathbf{f}}_{b,k-1} - \mathbf{f}_{b,k-1}^{\text{bias}}) + \mathbf{g} \right] \cdot \Delta t \\ \boldsymbol{\psi}_k &= \boldsymbol{\psi}_{k-1} + \boldsymbol{\Phi}_{b,k-1}^n \cdot (\tilde{\boldsymbol{\omega}}_{b,k-1} - \boldsymbol{\omega}_{b,k-1}^{\text{bias}}) \cdot \Delta t \end{aligned} \quad (1)$$

In Equation (1),  $\mathbf{r}$ ,  $\mathbf{v}$ ,  $\boldsymbol{\psi}$  are position, velocity and attitude (i.e., Euler angles) vectors (Euler angles) of the object in navigation frame;  $\Delta t$  is the sampling time;  $\tilde{\mathbf{f}}_b$  is the acceleration measurement vector from IMU (accelerometers);  $\tilde{\boldsymbol{\omega}}_b$  is the angular rate measurement vector from IMU (gyroscopes);  $\mathbf{f}_b^{\text{bias}}$  and  $\boldsymbol{\omega}_b^{\text{bias}}$  are the estimated accelerometer and gyroscope bias error terms;  $\mathbf{C}_b^n$  is the frame rotation matrix from body frame to navigation frame; and  $\boldsymbol{\Phi}_b^n$  is the rotation rate matrix between body frame and navigation frame, which are computed as:

$$\begin{aligned} \mathbf{C}_b^n &= \begin{bmatrix} c\phi c\theta & c\phi s\theta & -s\phi c\theta & c\phi s\theta & +s\phi s\theta \\ s\phi c\theta & s\phi s\theta & +c\phi c\theta & s\phi s\theta & -c\phi s\theta \\ -s\phi & c\phi s\theta & & c\phi c\theta & \end{bmatrix} \quad (2) \\ \boldsymbol{\Phi}_{b,k}^n &= \begin{bmatrix} 1 & s\theta t\phi & c\theta t\phi \\ 0 & c\theta & -s\theta \\ 0 & s\theta/c\phi & c\theta/c\phi \end{bmatrix} \end{aligned}$$

where  $cX = \cos X$ ,  $sX = \sin X$ , and  $\theta, \phi, \varphi$  represent the roll, pitch and yaw, respectively.

### B. Wi-Fi positioning approaches

Wi-Fi localization algorithms can provide absolute positioning solutions, which can be used in the correction steps of the integration system.

Three Wi-Fi localization approaches are considered in this paper: empirical RSS fingerprinting, WAF model based fingerprinting and simplified propagation model based positioning.

The fingerprinting algorithms are widely used for RSS based Wi-Fi localization. They operate in two distinguished phases: database building phase and location determination phase.

In the first phase, a database or radio map is constructed. It contains the signals emitted by the Wi-Fi Access Points (AP) on a grid of fix known positions. The database can be built by collecting real in-situation measurements or by using field propagation models (such as WAF model): the former is called empirical method while the latter is called propagation model (or WAF model) based method. The comparison and the analysis of these two methods are presented in [3].

In the second phase of location determination, the Weighted Nearest Neighbor in Signal Space (WNNSS) technique is used for both fingerprinting approaches introduced in this paper. The idea is to compute the weighted Euclidean distance  $d$  (in signal space) between the observed set of RSS measurements of the object

$RSS_{\text{OB}}$  and the RSSs at a fix set of locations recorded in database  $RSS_{\text{DB}}$ , which is expressed as:

$$d_i = \sqrt{\sum_{n=1}^m W_n (RSS_{\text{OB},n} - RSS_{\text{DB},n}^{(i)})^2}, \quad i \in I(j) \quad (3)$$

where  $m$  is the total number of available APs,  $I(j)$  is the location index set of database and  $W_n$  is the weight assigned to AP  $n$ .  $1/W_n$  is proportional to the standard deviation of the signal strength samples of AP  $n$ . Then the location  $i^*$ , i.e.,  $d_{i^*} = \min\{d_i \mid i \in I(j)\}$ , is picked for positioning the object.

Besides fingerprinting, Wi-Fi signal propagation model can be directly used as observation model for positioning. For instance, the WAF model, which is used in the second positioning approach, is a widely referred propagation model. It can be formulated as:

$$RSS_{\text{OB},n} = RSS_{\text{ref},n} - 10\alpha_n \log\left(\frac{\rho_n}{\rho_{\text{ref},n}}\right) - N_{w,n} \cdot WAF \quad (4)$$

where  $RSS_{\text{ref},n}$  denotes RSS from AP  $n$  at a reference point,  $\alpha$  is the signal decaying rate,  $\rho$  represents the distance between the object and the AP,  $\rho_{\text{ref}}$  is the distance between the reference point and the AP,  $N_w$  denotes number of walls in the signal path and  $WAF$  is the wall attenuation factor. With a pre-measured training dataset, the parameters can be estimated and then localization can be performed by using weighted least squares.

In contrast to the aforementioned approaches, for the third integration method introduced in this paper, a simplified propagation model is used as the observation model:

$$RSS_{\text{OB},n} = -10\alpha_n \log(\rho_n) + M_n \quad (5)$$

As shown in Equation (5),  $\alpha_n$  and  $M_n$  represent all the parameters of the signal propagation model from AP  $n$ . Both of them will be taken as parts of system state vector.

### C. Implementation of INS/Wi-Fi integrated systems using Unscented Kalman Filtering (UKF)

All three former mentioned systems use the INS process model as the system dynamic model (shown as Equation (1)). The state vector of the first and second systems is  $[\mathbf{r}^T \quad \mathbf{v}^T \quad \boldsymbol{\psi}^T \quad (\mathbf{f}_b^{\text{bias}})^T \quad (\boldsymbol{\omega}_b^{\text{bias}})^T]^T$ . The whole system dynamic model of the first and second systems can be expressed as:

$$\begin{aligned}
 \mathbf{r}_k &= \mathbf{r}_{k-1} + \mathbf{v}_{k-1} \cdot \Delta t + \mathbf{w}_{\mathbf{r},k-1} \\
 \mathbf{v}_k &= \mathbf{v}_{k-1} + \left[ \mathbf{C}_{b,k-1}^n \cdot (\tilde{\mathbf{f}}_{b,k-1} - \mathbf{f}_{b,k-1}^{\text{bias}}) + \mathbf{g} \right] \cdot \Delta t + \mathbf{w}_{\mathbf{v},k-1} \\
 \boldsymbol{\Psi}_k &= \boldsymbol{\Psi}_{k-1} + \boldsymbol{\Phi}_{b,k-1}^n \cdot (\tilde{\boldsymbol{\omega}}_{b,k-1} - \boldsymbol{\omega}_{b,k-1}^{\text{bias}}) \cdot \Delta t + \mathbf{w}_{\boldsymbol{\Psi},k-1} \\
 \mathbf{f}_{b,k}^{\text{bias}} &= \mathbf{f}_{b,k-1}^{\text{bias}} + \mathbf{w}_{\mathbf{f},k-1} \\
 \boldsymbol{\omega}_{b,k}^{\text{bias}} &= \boldsymbol{\omega}_{b,k-1}^{\text{bias}} + \mathbf{w}_{\boldsymbol{\omega},k-1}
 \end{aligned} \tag{6}$$

For the third method, propagation model parameter vectors  $\boldsymbol{\alpha}$  and  $\mathbf{M}$  should be added to the system state vector, and the following equations (Equation (7)) are added to the system dynamic model.

$$\begin{aligned}
 \boldsymbol{\alpha}_k &= \boldsymbol{\alpha}_{k-1} + \mathbf{w}_{\boldsymbol{\alpha},k-1} \\
 \mathbf{M}_k &= \mathbf{M}_{k-1} + \mathbf{w}_{\mathbf{M},k-1}
 \end{aligned} \tag{7}$$

The IMU bias errors  $\mathbf{f}_b^{\text{bias}}$  and  $\boldsymbol{\omega}_b^{\text{bias}}$  as well as propagation parameters  $\boldsymbol{\alpha}$  and  $\mathbf{M}$  are modeled as random walks plus constant in system dynamic models.

The first two systems employ a loosely-coupled integrated scheme. The absolute object positioning fixes are firstly derived using the fingerprinting localization methods, and they are used as measurements to update the INS estimates in the integrated systems.

The third system exploits a tightly-coupled integration approach, where the simplified propagation model is directly used in the system observation model. The observation model is formulated as:

$$\begin{aligned}
 RSS_{OB,1,k} &= -10\alpha_{1,k} \log(\rho_{1,k-1}) + M_{1,k-1} + v_{1,k-1} \\
 RSS_{OB,2,k} &= -10\alpha_{2,k} \log(\rho_{2,k-1}) + M_{2,k-1} + v_{2,k-1} \\
 &\vdots \\
 RSS_{OB,n,k} &= -10\alpha_{n,k-1} \log(\rho_{n,k-1}) + M_{n,k-1} + v_{n,k-1}
 \end{aligned} \tag{8}$$

with

$$\rho_{n,k} = \sqrt{(r_{x,k} - r_{AP(n),x,k})^2 + (r_{y,k} - r_{AP(n),y,k})^2 + (r_{z,k} - r_{AP(n),z,k})^2}$$

Due to the nonlinearities of the system state space models, the UKF is used instead of the conventional EKF in this paper.

#### D. Field experiments

The field experiments have been carried out inside a university building. The size of the test area is about  $25 \times 22$  meters. There are 5 available APs with known positions and 6 with unknown positions. A mobile robot will be used as the object that needs to be tracked. The Wi-Fi measurements are from a low cost Wi-Fi antenna (TP-Link TL-ANT2408C) and the inertial measurements are from a MEMS-based IMU (Xsens MTi).

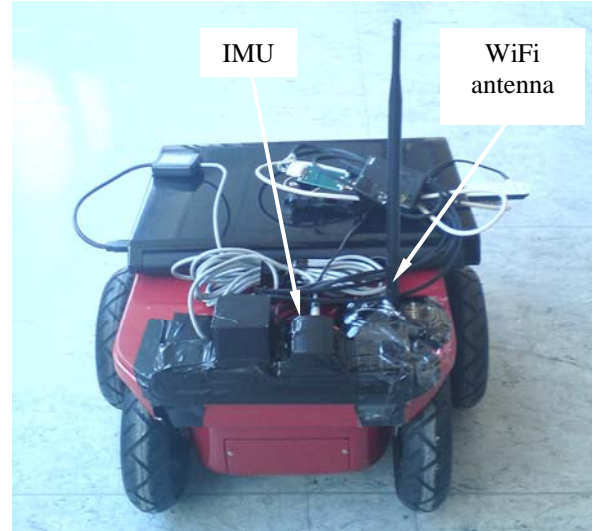


Figure 1. Experiment hardware

From the test results, it can be found that: the drift errors are unbound over time when using stand alone INS navigation; the integration systems can limit the INS drift errors and give an improved continuous navigation performance than the stand alone systems. The numerical results, as well as the comparison and analysis will be given in the full paper.

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