AP Detector: Crowdsourcing-based Approach for Self-localization of Wi-Fi FTM Stations

Yue Yu[1], Wenzhong Shi[1]*, Ruizhi Chen[2], Liang Chen[2]

1 The Hong Kong Polytechnic University, LSGI
2 Wuhan University, LIESMARS

Commission IV, WG IV/5

KEY WORDS: Self-localization, Wi-Fi APs, indoor pedestrian network, floor identification, bias estimation, iteration unscented Kalman filter.

ABSTRACT:

The acquisition of locations of Wi-Fi access points (APs) in urban buildings plays an important role in smart city applications, such as indoor navigation and social media data mining. This paper proposes a crowdsourcing-based approach for self-localization of Wi-Fi APs with the assistance of indoor pedestrian network (AP Detector). The features extracted from local opportunity signals are adopted for floor identification, and the crowdsourced indoor trajectories are segmented and matched with extracted indoor pedestrian network for the further trajectory calibration. In addition, the iteration unscented Kalman filter is applied for the location and bias estimation of local Wi-Fi FTM stations using the constructed Wi-Fi ranging model. The experimental results indicate that the proposed AP Detector can realize accurate location estimation of Wi-Fi APs, which also provides an effective way for autonomous construction of indoor navigation database and hybrid localization.

1. INTRODUCTION

The Wi-Fi based indoor localization has attracted attentions of many researchers because of its low cost and wide coverage characteristics. Various characteristics extracted from the Wi-Fi signals can be applied for indoor positioning purpose, for instance, received signal strength indication (RSSI) (Zhuang et al. 2015), channel impulse response (CIR) (Zhang et al. 2012), time of arrival (TOA) (He et al. 2013), time difference of arrival (TDOA) (Suraweera et al. 2020), angle of arrival (AOA) (Zafari et al. 2019), and channel state information (CSI) (Wang et al. 2016).

Aiming at the smartphone based indoor localization, most of above extracted characteristics are not supported due to the hardware or time synchronization based limitations. The Wi-Fi RSSI is the most commonly used wireless indoor positioning source, which usually contains two approaches: Wi-Fi ranging (Zhuang et al. 2015) and fingerprinting (Yu et al. 2021).

It can be found from state-of-art literatures that the smartphone Wi-Fi RSSI based ranging and fingerprinting methods are difficult to meet the requirements of meter-level indoor localization due to the changeable indoor environments and artificial interference. In order to improve the robustness of the Wi-Fi based positioning system (WPS), IEEE 802.11 standardized the Wi-Fi FTM protocol in 2016, which is hope to realize meter-lever round-trip-time (RTT) based ranging results between smartphones and Wi-Fi access points (APs) (IEEE, 2016).

(Choi et al. 2020) proposed a calibration-free system which integrates the RSS/FTM based ranging and PDR by the EKF algorithm, and the related parameters such as distortions in raw RTT, step-length, initial position and reference heading are optimized in real-time. The final integrated positioning accuracy is within 1.28 m in 75% in case of 40-MHz bandwidth. In a large-scaled indoor area, the locations of local Wi-Fi APs are always unknown or changeable because of the artificial interference, which leads to the difficulty of Wi-Fi ranging based localization (Nam et al. 2014). In addition, the initial ranging bias exists during the distance measurement procedure between different mobile terminals and Wi-Fi APs, which should also be detected and eliminated before localization phase (Yu et al. 2021).

This paper focuses on detecting the locations of local Wi-Fi APs which support the Wi-Fi FTM protocol and simultaneously calibrating the Wi-Fi FTM ranging bias. The contributions of this work are summarized as follows:

1) This paper proposes a crowdsourced trajectory estimation and optimization solution, which can realize accurate relative location and heading calculation results under magnetic interference and external acceleration contained environment.

2) This paper proposes a Long Short Term Memory network (LSTM) based floor identification algorithm, by extracting features from local opportunity signals and provides real-time floor indexes for crowdsourced trajectories.

3) This paper proposes trajectory partition and matching algorithm, which divides the crowdsourced trajectories into the combination of straight line and turning points, which can be further matched with extracted indoor pedestrian network to get the calibrated trajectory with high-precision.

4) This paper presents the hybrid Wi-Fi ranging model and iteration Uncented Kalman filter (iUKF) for Wi-Fi APs locations estimation and ranging bias calibration. The final experiments prove the precision and effectivity of proposed AP Detector framework.

This paper is organized as follows. Section II introduces the trajectory estimation, partition, matching, and calibration approach. Section III details the LSTM based floor identification and iUKF based Wi-Fi AP self-localization and ranging bias calibration. Section IV describes the experimental results. Section V concludes this paper.

2. CROWDSOURCED TRAJECTORIES PRE-PROCESS

In this part, a comprehensive crowdsourced trajectories pre-processing framework which contains trajectory modelling, partition, matching, and calibration is proposed to provide high-precision reference trajectory.

2.1 Trajectory Modelling and Segmentation

In this case, the state vector of trajectory estimation is modeled as follow:

$$\boldsymbol{X}_k = [p_x^k, p_y^k, p_z^k, \theta_k, b_k]^{\mathrm{T}} \tag{1}$$

where p_x^k, p_y^k, p_z^k represent the estimated 3D location of the pedestrian at the timestamp k, θ_k indicates the updated heading information, b_k indicates the heading bias. The state update equation is described as:

$$f(\boldsymbol{X}_t) = \begin{cases} p_x^{k-1} + \cos\theta_k \cdot L_k \\ p_y^{k-1} + \sin\theta_k \cdot L_k \\ p_z^{k-1} + \Delta h_k \\ \theta_{t-1} + \Delta T \cdot b_k \\ \exp(-\Delta T / T_c) \cdot b_{k-1} \end{cases} \tag{2}$$

where the heading bias b_k is regarded as a first-order Markov process, ΔT indicates the time interval between the adjacent steps, T_c is the correlation time, L_k indicates the real-time step-length, which is calculated by:

$$L_k = \delta_1 \cdot [0.7 + \delta_2 (H - 1.75) + \delta_3 \cdot \frac{(\beta_k - 1.79)H}{1.75}] \tag{3}$$

In which the δ_1, δ_2, δ_3 indicate the scale related parameters, β_k indicates the step frequency and H represents the pedestrian's height. The altitude information is provided by the integrated barometer sensor:

$$\Delta h_k = 44330 \cdot (1.0 - (\frac{100 p_t}{p_0})^{\frac{1.0}{5.255}}) \tag{4}$$

where Δh_k represents the calculated altitude change information, p_t and p_0 indicate the measured pressure at timestamp t and the basic pressure reference. In addition, the relative heading change information provided by the magnetometer during quasi-static magnetic field (QSMF) periods is adopted as the observation equation:

$$\tilde{\psi}_k - \hat{\psi}_0 = \delta\psi_k + n_\psi \tag{5}$$

where $\hat{\psi}_0$ and $\tilde{\psi}_t$ indicate the extracted magnetic heading at the first timestamp of the detected QSMF period and the magnetic heading at other QSMF epochs, n_ψ is the measured noise.

After the estimation of raw trajectory, the collected crowdsourced trajectories are segmented and divided into the combination of straight line and turning points. In this case, the modulus of gyroscope output is extracted:

$$Norm_{gyro}(t) = \sqrt{{g_x}^2 + {g_y}^2 + {g_z}^2} \tag{6}$$

where g_x, g_y, and g_z indicate the collected angular velocity of each axis. The turning point is detected based on the peak detection of modulus of gyroscope output, similar to the step detection procedure (Yu et al. 2019).

After detecting the turning points, the raw trajectory can be described as the combination of several segmentations:

$$\boldsymbol{Tra}_{\mathbf{segmented}} = \begin{pmatrix} x_1^1, y_1^1, \cdots, x_1^{w_1}, y_1^{w_1} & D_1 & \theta_1 \\ x_2^1, y_2^1, \cdots, x_2^{w_2}, y_2^{w_2} & D_2 & \theta_2 \\ \cdots & \cdots & \cdots \\ x_n^1, y_n^1, \cdots, x_n^{w_n}, y_n^{w_n} & D_n & \theta_n \end{pmatrix} \tag{7}$$

where x_n^1 and y_n^1 indicate the location coordinates contained in each trajectory segment, D_n represents the total distance of each trajectory segment, and θ_n indicates the estimated the fitted angle of each trajectory segment.

2.2 Trajectory Matching and Calibration

In our work, the indoor pedestrian network extracted from indoor map is applied as the prior knowledge of scenario, which also contains the combination of straight line and turning points:

$$\boldsymbol{Tra}_{\mathbf{refer}} = \begin{pmatrix} x_1^1, y_1^1, x_1^2, y_1^2 & D_1 & \theta_1 \\ x_2^1, y_2^1, x_2^2, y_2^2 & D_2 & \theta_2 \\ \cdots & \cdots & \cdots \\ x_n^1, y_n^1, x_n^2, y_n^2 & D_n & \theta_n \end{pmatrix} \tag{8}$$

where x_n^1 and y_n^1 indicate the intersection coordinates contained in each trajectory segment, D_n represents the total distance of each trajectory segment, and θ_n indicates the estimated the fitted angle of each trajectory segment.

Since the raw calculated trajectory contains only relative locations, thus the distance and fitted angle of each trajectory segment are selected for trajectory matching with the extracted indoor pedestrian network:

Table 1. Procedure of Crowdsourced Trajectory Matching

1) Extracting the adjacent points from the indoor pedestrian network and constructed the prior knowledge of scenario;

2) For i=1:Mst (Number of crowdsourced trajectories):

For j=1:Nst (Turning points): Compare the similarity between crowdsourced trajectory segmentation and reference segmentation:

$$\begin{aligned} \left\| D_n - D_n^{refer} \right\| \le Th_{01} \\ \left\| \theta_n - \theta_n^{refer} \right\| \le Th_{02} \end{aligned} \tag{9}$$

If: the Th01 and Th02 satisfy the set threshold, then search the next adjacent reference segmentation and record the

reference turning point, total distance and fitted angle of each trajectory segment.
end
end

3) While: one reference Trajectory is successfully detected:
For j=1:Nst (Turning points): Calibrate each segmentation of the raw trajectory according to the reference turning points, by rotating and scaling based on the comparison of the raw vector and the reference vector

$$\begin{aligned}\overrightarrow{AC_i} &= \overrightarrow{AB_i} \cdot \boldsymbol{P}_r \cdot \boldsymbol{C}_s \\ &= \overrightarrow{AB_i}\begin{bmatrix}\cos(\phi) & -\sin(\phi)\\ \sin(\phi) & \cos(\phi)\end{bmatrix}\begin{bmatrix}\gamma_x & 0\\ 0 & \gamma_y\end{bmatrix}\end{aligned} \tag{10}$$

where $\overrightarrow{AB_i}$ indicates the 2D location coordinates extracted from raw trajectory and $\overrightarrow{AC_i}$ is the pre-calibrated 2D location coordinates. ϕ represents the rotation angle, γ_x and γ_y, indicate the scale parameters of *x* and *y* axis.

3. WI-FI FTM STATIONS SELF-LOCALIZATION AND RANGING BIAS CALIBRATION

In order to provide an accurate performance of Wi-Fi FTM stations detection, the floor identification is required, and a comprehensive ranging and localization model is also needed for the final self-localization and bias calibration.

3.1 LSTM Based Floor Identification

To provide an autonomous floor identification function without any assist of additional facilities, the LSTM network is applied for floor identification using the features extracted from local opportunity signals, which can effectively decrease the effects of environmental interference in complex indoor areas. The extracted input features of the LSTM network are described as follows:

1) Number of effective Wi-Fi APs scanned from local environments: According to propagation characteristics of RSSI, the rate of change of signal attenuation gradually becomes less pronounced as the distance increases. Thus, in this part, the acquired RSSI values that larger than the set threshold would be regarded as the effective Wi-Fi APs:

$$V_{RSSI}(j) \geq \zeta_1 \tag{11}$$

where the $V_{RSSI}(j)$ indicates the received RSSI value of j^{st} Wi-Fi AP, and ζ_1 is corresponding threshold.

2) The most representative Wi-Fi APs: In this part, to describe the wireless characteristics of the specific indoor floor in detail, the RSSI vector acquired from the most representative Wi-Fi APs are modelled as the part of input value of LSTM network:

$$\{V_{RSSI}^1 \; V_{RSSI}^2 \; \cdots \; V_{RSSI}^k\} \geq \zeta_2 \tag{12}$$

where ζ_2 is corresponding threshold.

3) Average RSSI index of representative Wi-Fi APs: In this part, the average RSSI value of selected Wi-Fi APs is calculated as one of the input value of LSTM network:

$$V_{RSSI}^{Ave} = \sum_{i=1}^{k} V_{RSSI}^i \tag{13}$$

where V_{RSSI}^{Ave} indicates the calculated average RSSI index.

4) RSSI differences of representative Wi-Fi APs: In this part, the differences RSSI vector of selected Wi-Fi APs is also applied as input values of LSTM network:

$$V_{RSSI}^{Diff} = \left|V_{RSSI}^k - V_{RSSI}^{k-1}\right| \tag{14}$$

where V_{RSSI}^{Diff} indicates the RSSI difference index.

The output value of LSTM network is the floor index, the overall description of LSTM network is shown as:

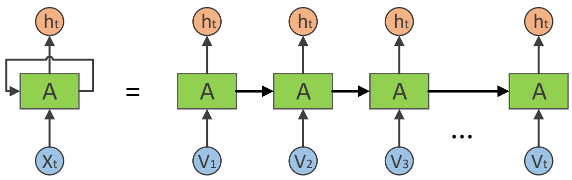

Figure 1. Description of LSTM network

3.2 System Model and Observation of AP Detector

In the proposed iUKF based AP detector, the state value contains two parts. The first part is the location of required Wi-Fi APs which need to be detected:

$$\delta\dot{\boldsymbol{X}}_s = \boldsymbol{F}_s \delta\boldsymbol{X}_s + \boldsymbol{G}_s \varepsilon_s \tag{15}$$

where $\delta\boldsymbol{X}_s$ is consist of the 2D locations of Wi-Fi APs which need to be detected, $\varepsilon_s = [\varepsilon_1 \cdots \varepsilon_{15}]$ indicates the error sources that comply the Gaussian distribution. $\boldsymbol{G}_s$ indicates the noise driven matrix.

The second part is the Wi-Fi FTM bias based error model. In our work, the bias of Wi-Fi FTM is applied to compensate the differences between different kinds of smartphones and Wi-Fi APs, which is modeled as the random walk process:

$$\dot{b}_{\mathrm{RTT}} = \varepsilon_{b_{\mathrm{RTT}}} \tag{16}$$

where $\varepsilon_{b_{\mathrm{RTT}}}$ is the white noise. The RTT bias based error model is described as:

$$\delta\dot{\boldsymbol{X}}_W = \boldsymbol{F}_W \delta\boldsymbol{X}_W + \boldsymbol{G}_W \varepsilon_W \tag{17}$$

where $\delta\boldsymbol{X}_W = b_{\mathrm{RTT}}$, $\boldsymbol{F}_W = 0$, $\boldsymbol{G}_W = 1$,and

$$\varepsilon_W = \varepsilon_{b_{\mathrm{RTT}}} \,.$$

As discussed in (Yu et al. 2020), the measured bias of Wi-Fi FTM depends on the types of smartphones and Wi-Fi APs. In addition, the measured RTT based distance is affected by both initial bias and environmental factors such as multipath propagation, NLOS, and random error. Thus, the raw ranging result can be modelled as follow:

$$L_{\mathrm{raw}} = L_{\mathrm{RTT}} + d_{bias} + d_E + d_{\mathrm{random}} \tag{18}$$

where L_{raw} indicates the smartphone reported distance; L_{RTT} represents; d_{bias} is the bias of Wi-Fi FTM which will be addressed in our paper; d_{E} is the environment related error; d_{random} represents the measured random error which is subjected to the Gaussian distribution.

The augmented form of Wi-Fi ranging bias calibration and self-localization state model is presented as:

$$\begin{bmatrix} \delta \dot{\boldsymbol{X}}_s \\ \delta \dot{\boldsymbol{X}}_W \end{bmatrix} = \begin{bmatrix} \boldsymbol{F}_s & 0 \\ 0 & \boldsymbol{F}_W \end{bmatrix} \begin{bmatrix} \delta \boldsymbol{X}_s \\ \delta \boldsymbol{X}_W \end{bmatrix} + \begin{bmatrix} \boldsymbol{G}_s & 0 \\ 0 & \boldsymbol{G}_W \end{bmatrix} \begin{bmatrix} \varepsilon_s \\ \varepsilon_W \end{bmatrix} \tag{19}$$

The observed model is described as:

$$\delta \boldsymbol{z}_d = \begin{bmatrix} \delta \boldsymbol{z}_{1,range} \\ \delta \boldsymbol{z}_{2,range} \\ \vdots \\ \delta \boldsymbol{z}_{m,range} \end{bmatrix} = \begin{bmatrix} d_{MEMS,1} - d_{FTM,1} \\ d_{MEMS,2} - d_{FTM,2} \\ \vdots \\ d_{MEMS,m} - d_{FTM,m} \end{bmatrix} \tag{20}$$

where $\delta \boldsymbol{z}_{m,range}$ indicates the ranging difference between Wi-Fi FTM and MEMS sensors based ranging estimation; The Wi-Fi FTM ranging model is defined in (18), and the MEMS sensors based ranging $d_{MEMS,m}$ is described as follow:

$$d_{MEMS,m} = \sqrt{(E^k_{_{MEMS}} - P^E_m)^2 + (N^k_{_{MEMS}} - P^N_m)^2} \tag{21}$$

where(E^k_{MEMS}, N^k_{MEMS}) indicates the MEMS sensors based localization result, (P_m^E, P_m^N) represents the location of the m^{st} Wi-Fi AP.

After completing each round of iUKF iteration, the calculated Kalman gain is extracted to evaluate the degree of convergence, if the value of Kalman gain reaches the convergence status, the whole procedure of iUKF will stop.

4. EXPERIMENTAL RESULTS

In this section, a series of experiments are designed to verify the robustness of the proposed AP detector framework. One typical office environment is selected as the experimental site. 4 Google Wi-Fi are deployed among different locations of one floor, which is shown in Figure 2. Google Pixel 3 and Google Pixel 4 are applied as the crowdsourced terminals to provide daily-life trajectories. The sampling rates of built-in sensors and Wi-Fi FTM are 50 Hz and 5 Hz.

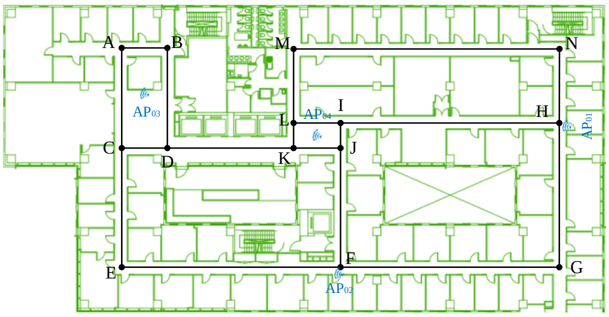

Figure 2. Walking Route and Deployment of Wi-Fi APs

4.1 Performance Evaluation of Trajectory Matching

In the procedure of crowdsourced trajectory modelling, the absolute location of the pedestrian is unknown because of the reference points are missing. In this case, a number of 45 initial daily-life trajectories are collected and only 25 trajectories are eligible, which contain at least three turning points and can be successfully matched with indoor pedestrian network. The raw collected crowdsourced trajectories are shown as:

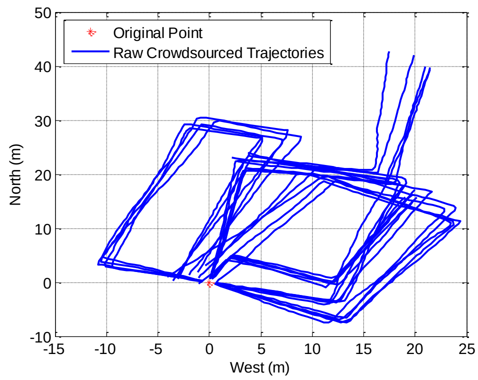

Figure 3. Description of Raw Crowdsourced Trajectories

In this work, trajectory matching algorithm is proposed for provide absolute reference of crowdsourced trajectories according to the fitted heading and length of trajectory segmentations. After the reference turning points are matched, the raw trajectories are calibrated and the corresponding floor plan can be constructed as:

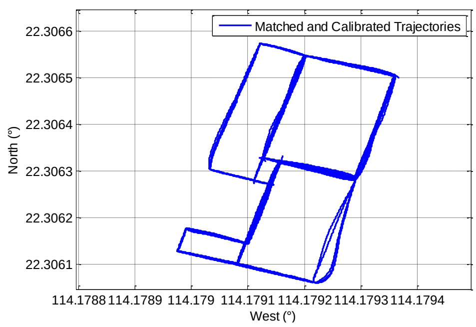

Figure 4. Matched and Calibrated Crowdsourced Trajectories

In addition, the accuracy of calibrated trajectories are compared with ground-truth indoor network, and the evaluated precision of calibrated trajectories is calculated as:

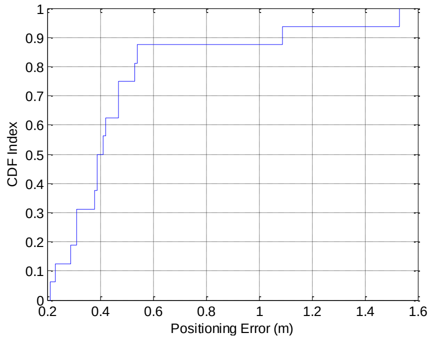

Figure 5. Accuracy of Calibrated Trajectories

It can be found from Figure 5 that the calibrated trajectories prove high-precision, and the overall trajectory error is within 0.47 m in 75%, which can further be applied for self-localization and bias estimation of local APs.

4.2 Performance Evaluation of Wi-Fi AP Self-localization and Calibration

After the calibration of crowdsourced trajectories, the self-localization and calibration solution is proposed for detecting the accurate locations of local APs which support the Wi-Fi FTM protocol. In this case, the crowdsourced points are selected according to the estimated accuracy of crowdsourced trajectories. The detection error of four Wi-Fi APs is described in Figure 6, and the estimated bias of Wi-Fi FTM is shown in Figure 7:

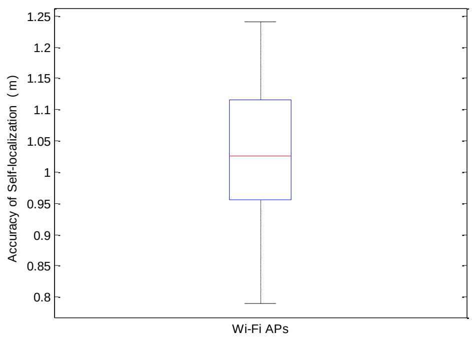

Figure 6. Detection Error of Wi-Fi APs

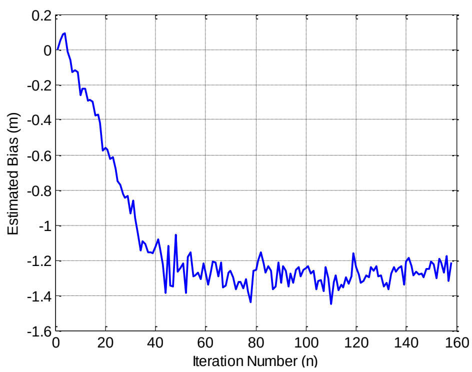

Figure 7. Estimated Bias of Wi-Fi APs

It can be found from Figure 6 and Figure 7 that the accuracy of Wi-Fi AP detection reaches 1.12 m in 75%, and the estimated Wi-Fi ranging bias also reaches a state of convergence.

4.3 Performance Evaluation of Floor Identification and Multi-source Fusion Based Localization

In this work, the LSTM based floor detection algorithm is proposed to provide floor index for crowdsourced trajectories before trajectory matching procedure. To cover the required indoor areas, 30 different trajectories collected from 4 different floors are applied for training phase, and 20 trajectories are applied as the test dataset, and the overall detection accuracy of different floors are described as:

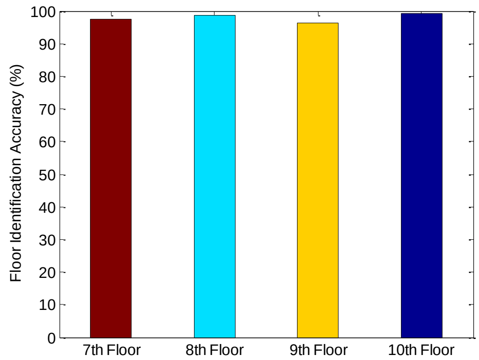

Figure 8. Accuracy of Floor Identification

It can be found from Figure 8 that the proposed LSTM based floor detection algorithm proves high precision, which reaches an average accuracy of more than 98% according to the test dataset on different floors.

Finally, the detected locations and bias of Wi-Fi FTM stations are used for real-time indoor localization, in this case, the tester started from the point A, passed by the points C, J, F, G, H, I, F, E, and returned to the point A. To evaluate the positioning error using different approach, the absolute location is provided for the sensors based localization approach, the overall trajectory comparison between sensors approach by trajectory modelling, and the UKF based multi-source fusion model (Yu et al. 2019) is shown in Figure 9:

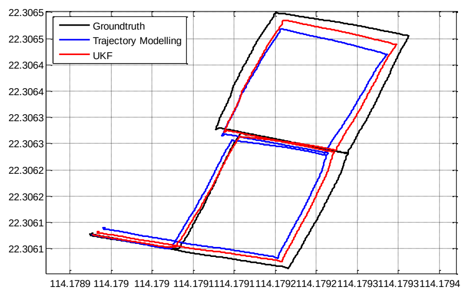

Figure 9. Accuracy of Floor Identification

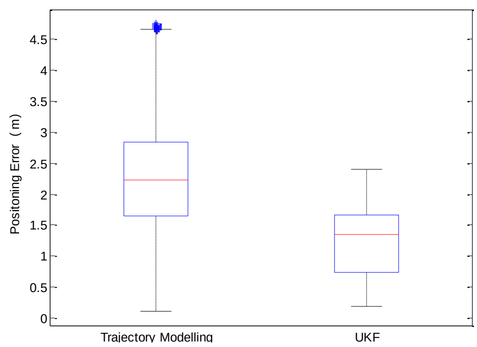

Figure 10. Accuracy of Floor Identification

It can be found from Figure 10 that the proposed Wi-Fi AP detection framework can finally realize the autonomous indoor localization by detecting the locations and biases of Wi-Fi APs and providing absolute reference to built-in sensors. The estimated positioning accuracy reaches 1.67 m in 75%, compared with the raw built-in sensors within 2.85 m in 75%. Thus, the proposed AP detector provides an autonomous approach for self-localization and bias calibration of local Wi-Fi FTM stations using crowdsourced trajectories and indoor pedestrian network, which can further be applied for universal indoor localization.

5. CONCLUSION

In order to realize the self-localization and bias estimation of Wi-Fi APs which support the FTM protocol, this paper proposes the AP Detector framework, which contains three main parts: (1) Crowdsourced trajectory modeling and optimization, which can be applied under the magnetic interference and external acceleration contained indoor environments; (2) Crowdsourced trajectories matching and calibration with the assist of the extracted indoor pedestrian network, which can realize an overall floor plan construction accuracy of 0.47 m in 75%; (3) LSTM based floor identification and iUKF based APs self-localization and bias calibration, which finally realize the an average floor detection precision of more than 98% and AP self-localization accuracy of 1.12 m in 75%, the final real-time positioning error using detected APs and bias reaches 1.67 m in 75%.

ACKNOWLEDGEMENTS

This work was supported by The Hong Kong Polytechnic University (1-ZVN6, 4-BCF7); The State Bureau of Surveying and Mapping, P.R. China (1-ZVE8); and Hong Kong Research Grants Council (T22-505/19-N).

REFERENCES

Zhuang, Y., Syed, Z., Li, Y., & El-Sheimy, N. (2015). Evaluation of two WiFi positioning systems based on autonomous crowdsourcing of handheld devices for indoor navigation. *IEEE Transactions on Mobile Computing*, 15(8), 1982-1995.

Zhang, D., Liu, Y., Guo, X., Gao, M., & Ni, L. M. (2012, March). On distinguishing the multiple radio paths in rss-based ranging. *In 2012 Proceedings IEEE INFOCOM* (pp. 2201-2209). IEEE.

He, Z., Ma, Y., & Tafazolli, R. (2013). Improved high resolution TOA estimation for OFDM-WLAN based indoor ranging. *IEEE Wireless Communications Letters*, 2(2), 163-166.

Suraweera, N., Li, S., Johnson, M., Collings, I. B., Hanly, S. V., Ni, W., & Hedley, M. (2020). Environment-assisted passive WiFi tracking with self-localizing asynchronous sniffers. *IEEE Systems Journal*, 14(4), 4798-4809.

Zafari, F., Gkelias, A., & Leung, K. K. (2019). A survey of indoor localization systems and technologies. *IEEE Communications Surveys & Tutorials*, 21(3), 2568-2599.

Wang, X., Gao, L., Mao, S., & Pandey, S. (2016). CSI-based fingerprinting for indoor localization: A deep learning approach. *IEEE Transactions on Vehicular Technology*, 66(1), 763-776.

Zhuang, Y., Li, Y., Lan, H., Syed, Z., & El-Sheimy, N. (2015). Wireless access point localization using nonlinear least squares and multi-level quality control. *IEEE Wireless Communications Letters*, 4(6), 693-696.

Yu, Y., Chen, R., Chen, L., Li, W., Wu, Y., & Zhou, H. (2021). Autonomous 3d indoor localization based on crowdsourced wi-fi fingerprinting and mems sensors. *IEEE Sensors Journal*.

IEEE Computer Society LAN/MAN Standards Committee. IEEE Standard for Information Technology-Telecommunications and Information Exchange Between Systems—Local and Metropolitan Area Networks—Specific Requirements Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications, IEEE Standard 802.11, 2016.

Choi, J., & Choi, Y. S. (2020). Calibration-free positioning technique using Wi-Fi ranging and built-in sensors of mobile devices. *IEEE Internet of Things Journal*, 8(1), 541-554.

Nam, S. Y. (2014). Localization of access points based on signal strength measured by a mobile user node. *IEEE Communications letters*, 18(8), 1407-1410.

Yu, Y., Chen, R., Chen, L., Li, W., Wu, Y., & Zhou, H. (2021). H-WPS: Hybrid Wireless Positioning System Using an Enhanced Wi-Fi FTM/RSSI/MEMS Sensors Integration Approach. *IEEE Internet of Things Journal*.

Yu, Y., Chen, R., Chen, L., Guo, G., Ye, F., & Liu, Z. (2019). A robust dead reckoning algorithm based on Wi-Fi FTM and multiple sensors. *Remote Sensing*, 11(5), 504.

Yu, Y., Chen, R., Liu, Z., Guo, G., Ye, F., & Chen, L. (2020). Wi-Fi fine time measurement: Data analysis and processing for indoor localisation. *The Journal of Navigation*, 73(5), 1106-1128.