Enhancement of Robustness and Precision of Indoor Positioning by Fusing Wifi Fingerprinting and Pdr Techniques

Muhammad Shahid Jabbar, Ghulam Hussain, Jundong Cho, Sangmin Bae

***Abstract*: Fused approaches for enhancing robustness and precision of indoor positioning using pedestrian dead reckoning (PDR) and KNN (K-Nearest Neighbors) classifier based WiFi fingerprinting were proposed. The proposed machine learning approaches employed the rough position estimate by PDR as a pre-sorter of training vectors of KNN classifier and help improve precision by overcoming fluctuating radio signal and furthermore robustness in serious radio signal distortion by the undesired malfunction of WiFi signal sources. The experiment in real space showed significant improvement in both precision and robustness.**

***Index Terms*: fusion with fingerprinting and PDR; K-Nearest Neighbors algorithm; machine learning; pedestrian dead reckoning (PDR) algorithm; robust-ness and precision in indoor positioning; WiFi fingerprinting indoor positioning.**

I. INTRODUCTION

Indoors localization and navigation are active research topic of emerging appeal for location-based context aware services, ubiquitous connectivity and leveraging internet of things (IoT). The subject of this paper is about indoor location technologies for human using handheld devices such as smartphones. Use of smartphone-based methods is prominent in existing indoor localization techniques, also WiFi access points (AP) use in buildings is prevalent. Hence deployment of new infrastructure is not required for WiFi fingerprinting, where smartphone measures the received signal strength intensity (RSSI) of installed APs. WiFi fingerprinting comprises of offline and online phase, a site survey for access points RSSI is conducted at all training points in offline phase and stored into the server where online test RSSI measurement are compared based on nearest neighbor or other algorithms to output position estimates as in [1]. Triangulation and Trilateration based methods estimate distance between AP and test point by RSSI but their application is limited as they require line of sight measurements. WiFi signal reception at any particular point is not wide sense stationary also fingerprinting performance is hugely hampered by obstacles and multipath fading. Offline site survey prior to use is another constraint which needs trained labor. Also, any changes at site might need re-calibration of offline phase [2].

Another popular method employs accelerometer, gyroscope and magnetometer sensors built into most smartphones. This technique incorporates pedestrians heading direction and distance hence called pedestrians dead reckoning (PDR) so that no site survey and APs are required. After detecting a step through accelerometer, PDR calculates step count and average step length yielding moving distance which combined with gyroscope sensor data provides walking trajectory and final position [3]. However, PDR assumes walking pattern and step lengths to be consistent, it also has the issues of pedestrian and smartphone heading direction misalignment and even the best algorithms works for a number of constrained poses for holding smartphone while walking such as handheld, back pocket and swinging in hand. Low quality smartphone sensors as well as unpredictable and free style walking make these problems worse hence real-world applications are limited.

Loss, attenuation or interference from one or more AP signals affects the test RSSI vector which leads to erroneously predict the user position. Accumulation of step length estimate error over long trajectories and angle misalignment error also affect the robustness of system. A system is said to be robust in localization if it correctly estimates user position by compensating above cases whereas precision is the scatter of estimated position deviation from true position. As robustness and precision are affected by each of WiFi fingerprinting and PDR techniques, the two methods could be positively fused to enhance robustness and precision. Several fusion algorithms have been proposed to compensate the limitations of WiFi fingerprinting and PDR techniques In this paper we have presented two novel fusion algorithms and investigated the problem for robustness.

II. BACKGROUND

Global Navigation Satellite System (GNSS) signals cannot penetrate inside buildings so indoor localization solutions have prevalent commercial potential. There has been immense research on movement tracking [11] and signaling based systems mainly through WiFi APs for the ease of implementation as in [1, 2]. Non-smart phones-based method also constitute localization research but they have the disadvantage of higher setup costs due to new infrastructure. Few hybrid techniques have also been developed fusing motion sensors data with fingerprinting to improve target estimation accuracy. Kalman Filter (KF) has been employed for fingerprinting and PDR fusion joint probability distribution overtime to produce location estimates. KF might need more context and system model

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information [4] beyond PDR and fingerprinting such as [5] re-quired landmark and map information. They are computationally efficient and produce better location estimates assuming linear Gaussian models however real-world scenarios and smartphone motion sensors noise models and walking patterns are rather com-plex for KF to effectively solve localization problem. On the other hand, Particle Filters [6] are more suitable for non-linear noise and walking pattern problem by computing posterior distributions for position estimates [7, 8] but with high computational cost and energy consumption. K-weighted nearest neighbor (KWNN) based algorithms have also been developed as they required no noise model information in contrast to Kalman and Particle filters. KWNN is used with fingerprinting data and resulting estimates are then reinforced by combining PDR measurements [9], whereas PDR and fingerprinting measurements are directly combined with KWNN in [10].

Proposed fusion algorithms in this paper works based on rough position estimate by PDR and eliminating irrelevant, i.e., far away reference points (RP), and compensation of WiFi signal degradation. They require no noise parameters and site models and are low complexity so it is very practical to be used by smartphones. Further-more, in case of loss of any particular sensor data or loss or degradation of WiFi access point signals, our system has been tested through various experiment conditions to perform in more robust manner.

III. STATEMENT OF PROBLEM

WiFi was designed solely for data communication which leaves less room for its precise and robust localization applications. Its performance is further limited by heterogeneous nature of test devices, non-WSS (wide sense stationary) signal characteristics, signal outliers, multipath fading, obstacles and humans obstructing line of sight measurements result in biased position estimates.

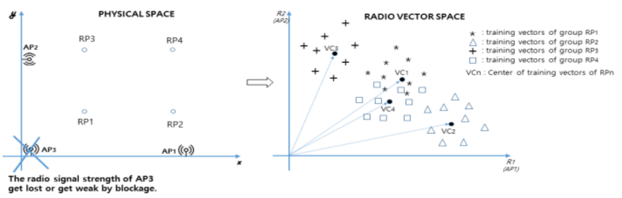

Fig. 1 Illustration of radio vector space and robustness

Consider the simple environment with three APs depicting 4 RPs physical arrangement as, when we analyze the RSSI at each RP, the radio signal vector space with only AP1 and AP2 can be drawn with respective center of group RPs as in Fig. 1. Note that the physical distance between RPs do not correspond to the center of RP distances, notated as VC1~VC4 (Center of radio vectors belong to same RP), in vector space i.e. two RPs may be far apart in physical space but may be overlapping in radio signal vector space which makes it abstruse for classifiers to output true location. In case of any obstacle between any certain position and AP, the radio measurement drops toward corresponding AP axis in radio vector space depending upon nature of obstacle. The inherent fluctuating characteristic of WiFi radio signal results in poor performance in terms of precision as resultant RP measurements in radio vector space keeps fluctuating when fingerprinting applies for location. Devastating cases occur when some of APs are out of order and the location service keeps being provided before the malfunctioning is fixed. Although many solutions have been proposed but they need knowledge of either noise parameters, indoor site map or perform only when all sensors data and AP signals are provided. Fusion algorithms also suffer when PDR drops accuracy over long distance trajectories due to error accumulation even though fingerprinting is working. This demands algorithms where output confidence is not weighted over both fingerprinting and PDR but fingerprinting estimates needs to be finely and locally tuned by PDR sensor data so that system is less prone to fail in real-world implementations.

IV. PROPOSED ALGORITHM

The conventional KNN classifier for WiFi fingerprinting positioning requires measurement of RSSI vectors from all WiFi APs at each RP, stored as “training vectors”. The position of each RP in 2-dimensional space given by $L_{RP,n} = (x_{RP,n}, y_{RP,n}), n = 1...N$ in Cartesian coordinates is stored as “training positions”. The training vectors and training positions of RPs are used for classification. Notice that for each of “N” RPs, there could be multiple training vectors, “M” denoting numbers of RSSI vectors, are measured as training vectors at an RP, and the training vectors share the same training position of the RP. There will be total $M \times N$ training vectors, $\overline{r_i}, i = 1$. The size of “training positions” can be extended to $M \times N$, that is $L_{RP,n} = (x_{RP,n}, y_{RP,n}),\ n = 1...MN$ for the convenience, with having the same position at the same RP.

At every predefined unit of time for which a user makes short movement, RSSI’s from APs are measured to comprise a “test vector”. K nearest training vectors are chosen based on RSSI vector distance between the test vector and each of training vector. The vector distance is calculated as below, for example, in case of Euclidean distance and sorted.

$$e_i = (\sum_{l=1}^{L}(r_{l,i} - r_m)^2)^{1/2}, i = 1...MN \tag{1}$$

Where L is number of WiFi AP, z_l is the RSSI measurement for l th AP, $r_{l,i}$ is RSSI components of i th training vector for l th AP. In the conventional KWNN (K weighted nearest neighbors) classifier, the current position is estimated with weighted sum of corresponding RP positions of the nearest training vectors as below.

$$(x_e, y_e) = (\sum_{i=1}^{K} w_i x_{RP,i}, \sum_{i=1}^{K} w_i y_{RP,i}) \tag{2}$$

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$$w_i = \frac{1/e_i^p}{\sum_{j=1}^{K} 1/e_i^p}$$

Where, is distance weight.

In proposed fusion approaches, the K nearest neighbors are selectively chosen from the training vectors, based on the estimated position by PDR prior to calculation of vector distance as in the conventional KNN. In order to selectively choose the neighbors, another weight value $v_i, i = 1 \ldots N$ is introduced where N is number of RPs.

Let the position estimation by PDR be $L_{pdr} = (x_p, y_p)$, then;

A. Fusion A

The weight v_i is defined as

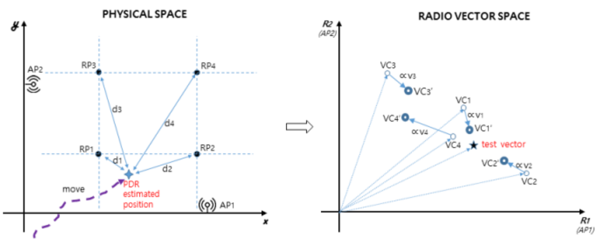

Fig. 2 PDR estimation assisted fingerprinting positioning

$$v_i = \begin{cases} 1, \; if \;\; dist(L_{pdr} - L_{RP,i}) < Th_a \\ 0, \; else \end{cases}, \; for \; i = 1 \ldots N \tag{3}$$

Where, Tha is a threshold which required to be determined empirically. The vi has non-zero value only when the physical distance between PDR estimated position and each RP is less than the threshold. Then the vector distance ei is replaced with viei before sorted for finding nearest training vectors. This algorithm effectively eliminates the far RPs and limits the search to the RPs neighboring located within threshold.

B. Fusion B

The weight vi is defined as proportional to position distance between PDR estimated position and each RP as in Fig. 2.

$$v_i = a_b \times dist(L_{pdr} - L_{RP,i}), \; for \; i = 1 \ldots N \tag{4}$$

Where, a_b is a scaling factor. Then, the vector distance ei is replaced with viei before sorted for finding nearest training vectors. The algorithm detail is as follows;

1. Move to next position.
2. Estimate current position with PDR estimation, called (x_p, y_p).
3. Calculate physical distance, d_i, between PDR estimate position (x_p, y_p) and all RP positions (x_p, y_p), i=1~N_{RP}, Where the N_RP is the total number of RPs.
4. Determine distance weight $w_{d,i}$, which is proportional to the d_i.
5. Measure WiFi RSSI vector of APs, called $\bar{z}$, which is "test vector" for KNN.
6. Vector distances between all training vectors belong to RPs and $\bar{r}$ are calculated, and weighted by $w_{d,i}$. This means that the vector distance to the training vector of a RP increases or decreases, proportionally to the distance between the PDR estimated position and the position of the corresponding RP at physical space.
7. Performs KNN with test vector and training vector having weights and decide the position by averaging physical position of K neighboring RPs.

In summary, in the proposed algorithms, the PDR estimate plays role as filter (Fusion A) or sorter (Fusion B) of neighbors prior to KNN classification. It helps recover the distorted posterior probability distribution of true neighbors.

The proposed approaches can be analyzed statistically. In the conventional KNN classifier, searching for the nearest neighbors based on RSSI measurements is a maximum a posteriori (MAP) estimation where the measured RSSI $\bar{z}$, is an observation and training vectors, $\bar{r}_i, i = 1 \ldots N$, are corresponding to hidden states, which is represented as follows.

$$\arg\max_i P(\bar{r}_i \mid \bar{z}) = \arg\max_i \frac{P(\bar{z} \mid \bar{r}_i) P(\bar{r}_i)}{P(\bar{z})} \tag{5}$$

where the $P(\bar{r}_i \mid \bar{z})$ is a posteriori (MAP) probability, and the $P(\bar{z} \mid \bar{r}_i)$ is a likelihood probability, and the a priori probability $P(\bar{r}_i), i = 1 \ldots N$, are assumed to be equally likely when the RP positions are unknown.

In the proposed fusion approaches, the a priori probability $P(\bar{r}_i)$ is intentionally biased to make the neighbors belongs to RPs close to PDR estimation have bigger probabilities, so it is not equally likely anymore. Therefore, in the proposed approaches, the probability $P(\bar{r}_i)$ at the Bayesian estimation (3) is replaced with $P'(\bar{r}_i)$ defined as follows;

for Fusion A,

$$P'(\bar{r}_i) = \begin{cases} 1/K, \; if \;\; dist(L_{pdr} - L_{RP,i}) < Th_a \\ 0, \; else \end{cases}, \; for \; i = 1 \ldots N \tag{6}$$

and, for Fusion B,

$$P'(\bar{r}_i) = \beta_b / dist(L_{pdr} - L_{RP,i}), \; for \; i = 1 \ldots N \tag{7}$$

where the β_b is a scaling factor, with the condition that $\sum_i P(\bar{r}_i) = 1$. When the likelihood probability $P(\bar{z} \mid \bar{r}_i)$ is distorted or time-variant, the a priori probability $P'(\bar{r}_i)$ helps compensate it, hence, and recover the overall performance of the Bayesian estimation.

V. EXPERIMENT RESULTS AND ANALYSIS

Extensive experiments were performed in a typical office environment to resemble real application scenario, comprising of three offices and corridor of about 130m2 area on the same floor as in Fig. 3. Smartphones gyroscope sensor yaw angle and accelerometer data was collected for six distinct trajectories. Step detection, average step length, step count and heading angle are calculated to obtain trajectory's destination coordinates for PDR. In order to train the KNN algorithm, 276 measurements of WiFi AP's

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Table 1 No Fusion (Conventional KNN) Experimental Results

Parameter	Test case I (No signal degradation)			Test case II (Two AP signals are degraded by 10dB)			Test Case III (One AP is lost)		
Number of neighbors (K)	4	5	6	4	5	6	4	5	6
E( ) (cm)	50	54	58	134	134	134	319	321	326
σ( ) (cm)	81	77	75	114	106	101	191	188	190
error rate (%)	12.3	22.1	19.9	47.8	55.8	52.5	83.0	89.9	88.0

Table 2: Fusion A (with K=5) Experimental Results

Parameter	Test case I (No signal degradation)			Test case II (Two AP signals are degraded by 10dB)			Test Case III (One AP is lost)		
(cm)	10	50	100	10	50	100	10	50	100
E( ) (cm)	7	14	46	25	33	63	54	72	112
σ( ) (cm)	18	31	75	39	46	76	43	53	83
error rate (%)	8.3	9.4	21.7	27.2	28.6	36.6	44.9	47.5	55.2

Table 3: Fusion B (with K=5) Experimental Results

Parameter	Test case I (No signal degradation)			Test case II (Two AP signals are degraded by 10dB)			Test Case III (One AP is lost)		
(cm)	10	50	100	10	50	100	10	50	100
E( ) (cm)	0	8	62	0	18	79	0	20	98
σ( ) (cm)	0	29	82	0	46	92	0	50	91
error rate (%)	**0**	**2.2**	**29.7**	**0**	**10.5**	**38.9**	**0**	**11.1**	**53.3**

signals are collected. Each measurement consists of the RSSI values of 7 AP's. There are 46 reference positions (RP) and six measurements per RP are collected. That is, length of reference vectors for training are 7, and there are 6 training vectors per RP, and are total 276 training vectors. After training, another set of 276 measurements are collected, as test vectors, for testing the proposed algorithm. Same set of test vectors are used for comparing proposed algorithms (Fusion A and Fusion B) to the conventional KNN algorithm, here it is called "No Fusion".

Test case I: A group of measurements, test vectors, are collected for testing at different time, with which all WiFi AP's are functioning well. This test case is for measuring the system performance in terms of "accuracy (average of error distance of estimated position from true position)" and "precision (standard deviation of the deviation)" both.

Test case II: The amplitude of AP3 and AP7 signals of the test vectors are degraded by 10dB. This kind of signal degradation happens easily and frequently in real world by unintentional .

Test case III: The AP7 is lost, i.e. there is no radio signal from AP7. The AP signal can be lost anytime by unexpected power loss or device malfunction, which is hard to be recognized until regular system checking cycle.

Overall, when Fusion A and Fusion B are applied, the performance is improved significantly than that of "No Fusion' case. Here, σpdr is the standard deviation of Euclidean distance between true positions and PDR estimated positions, assuming the probability of PDR estimation position has a normal distribution. de is the error distance between true position and estimated position, where true positions being the position of RPs. The estimated position is average position of the closest K neighbors. E(de) is average value of $d'_e s$ and σ(de) is standard deviation of $d'_e s$. And "error rate" is the rate of mismatch when majority of closest neighbors found by KNN do not belong to the true RP. No Fusion, Fusion A and Fusion B results are provided in Table 1, 2 and 3 respectively. The performance of the two Fusion algorithms is superior in normal case and in both abnormal situations: one of AP's are lost or two AP signals are 10dB degraded by unexpected blockage.

The conventional KNN classifier using only WiFi RSSI vectors, even when there are no signal defects, may show poor performance because of time-varying characteristics of WiFi radio signal. Comparing the performance of Test case I, it shows that the accuracy (E(de), average value) and precision (σ(de), standard deviation) are improved significantly by the fusion algorithms. We found also that optimizing number of neighbors and method of calculating distance weight also can improve the performance in some extent.

However, it is not still satisfactory when the part of WiFi signal sources is impaired by unexpected incidents in which the positioning system requires robustness. The experiment results show the performance in terms of robustness is improved by proposed approaches. For example, at K=5, without the Fusion algorithms, the average of error distance (i.e. accuracy) increases from 54 to 134 when two AP signals are degraded. However, it is increased by only 19, from 14 to 33, when the Fusion algorithms applies.

Observing the performance of Fusion B algorithm, if we can use PDR estimated position together even if the accuracy is not perfect, the performance of KNN is enhanced significantly. When the estimated position of PDR is within 50cm, the Fusion B shows better performance than Fusion A in both abnormal situations, while PDR estimate be worse to 100cm, both fusion algorithms shows similar performance.

In conclusion, it is shown that the proposed fusion algorithms show robustness in unexpected AP signal faults.

VI. CONCLUSION

In this paper, we proposed novel PDR compensated WiFi finger-printing algorithms for indoor positioning and demonstrated performance enhancement in precision and robustness, and further in accuracy, with experimental results. They can be used with existing WiFi infrastructure and smartphone sensors, also it needs no noise parameters knowledge of smartphone motion sensors and has less computational cost. Fusion A eliminates improbable reference points from WiFi fingerprinting nearest neighbors. Fusion B compensates the error between the estimated values of distance vectors and predicts user position. Both fusion algorithms perform better in terms of accuracy as well as precision, and are much more robust than conventional KNN in test conditions of all three cases: no WiFi signal degradation, attenuation by 10db in two AP signals and loss of one AP signal, with limitation of PDR estimated position accuracy in certain range which should be improved in future work. Ap-propriate metrics for measuring and generalizing the performance of robustness in terms of degree of system impairment are required to be developed in future study.

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REFERENCES

1. S. He and S.-H. G. Chan, "Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 466–490, 2016.
2. A. Khalajmehrabadi, N. Gatsis, and D. Akopian, "Modern WLAN Fingerprinting Indoor Positioning Methods and Deployment Challenges," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 3, pp. 1974–2002, 2017.
3. J. Kuang, X. Niu, and X. Chen, "Robust Pedestrian Dead Reckoning Based on MEMS-IMU for Smartphones," *Sensors*, vol. 18, no. 5, p. 1391, Jan. 2018.
4. Shoewu, O., G. Anuforonini, and O. Duduyemi. "Simulation of the Performance of CdTe/CdS/ZnO Multi-Junction Thin Film Solar Cell." Review of Information Engineering and Applications 3.1 (2016): 1-10..
5. D. Han, S. Jung, M. Lee, and G. Yoon , "Building a Practical Wi-Fi-Based Indoor Navigation System," *IEEE Pervasive Computing*, vol. 13, no. 2, pp. 72–79, 2014.
6. M.S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, 2002. "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *IEEE Transactions on Signal Processing*, pp 174–188, 2002.
7. Nayyar, Anand, and Vikram Puri. "Comprehensive Analysis & Performance Comparison of Clustering Algorithms for Big Data." Review of Computer Engineering Research 4. 2 (2017): 54-80.
8. Anuforonini, G., and O. Duduyemi. "Simulation of the Performance of CdTe/CdS/ZnO Multi-Junction Thin Film Solar Cell." Simulation 3. 1 (2016): 1-10.
9. M. Jin, B. Koo, S. Lee, C. Park, M. J. Lee, and S. Kim, "IMU-assisted nearest neighbor selection for real-time WiFi fingerprinting positioning," *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2014.
10. Ali, A., & Haseeb, M. (2019). Radio frequency identification (RFID) technology as a strategic tool towards higher performance of supply chain operations in textile and apparel industry of Malaysia. *Uncertain Supply Chain Management, 7*(2), 215-226.
11. Z. Xiao, H. Wen, A. Markham, and N. Trigoni, "Robust Indoor Positioning With Lifelong Learning," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2287–2301, 2015.