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Indoor People Counting Method based on Fingerprinting Localization with Kernel Fuzzy C-Means Clustering

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***Abstract*—Efficient and accurate people counting has become significant as it is essential in many applications such as smart guide and intelligent building. In this paper, a people counting approach based on fingerprinting localization is proposed for multiple regions in indoor environment. We obtain the number of people in each subarea by localizing each target in the environment. The approach is composed of the offline training phase and online counting phase. In offline phase, we construct the fingerprint database which is also called radiomap, and transform it through DIFF method to solve the problem of device diversity. Then we divide the whole region into different subareas utilizing Kernel Fuzzy C-Means (KFCM) Clustering algorithm to reduce the computational complexity. In online phase, we first select the nearest subarea of the target and then estimate its location. The location is compared with the boundaries of all subareas to determine the subarea it belongs to. When applied to multiple targets, the number of people in each region will be counted. Experimental results show that our proposed method is effective and the average people counting accuracy can achieve 90.24%.**

Keywords-People Counting; Indoor localization; Fingerprinting; Kernel Fuzzy C-Means Clustering

I. INTRODUCTION

People counting means counting or estimating the number of people within a region. It can be applied in many places such as markets and museums. Real-time people counting for these places helps to understand the distribution of people and provide reliable basis for resource management, decision analysis and security. Various approaches have been proposed for people counting at present, which can mainly be classified into two categories: video-based and radio-based.

Researches on video-based people counting have been conducted. Yam et al. [1] proposed an object based bi-directional counting system, which combined feature matching and point line distance techniques on the object and the detection line respectively. Xu et al. [2] proposed an approach using the mixture of dynamic-texture motion model to address the problem of crowd size estimation. Many recent studies used Histogram of Oriented Gradient (HOG) technique for people counting. However, most of the video-based approaches have some disadvantages. First, cameras can only work under line-of-sight conditions. Second, the deployment and computational costs of video-based systems are high. Furthermore, the use of cameras may raise concerns of privacy issues.

Radio-based researches make use of signals such as radio frequency identification (RFID) [3,4] and Wireless-Fidelity (Wi-Fi) [5-7]. Radio-based systems can be further classified into device-based and device-free systems. In device-based systems, counting is performed by counting the number of people carrying devices such as RFID tags or mobile devices. Device-free counting indicates the estimation without any devices attached to the target. In such systems, counting is performed by detecting changes in the wireless environment. Li et al. [5] analyzed the relationship between the Wi-Fi signals and the number of people using five-layer neural network model. Ahmed et al. [7] proposed a knowledge model driven system which consist of signal propagation model, K-Means clustering and Support Vector Machine (SVM) classifier for people counting and coarse level localization based on received signal strength indication (RSSI). Xu et al. [8] made use of successive cancellations to iteratively determine the number of subjects. More recent researches used channel state information (CSI) measurements to describe channel properties of the communication link [6,9].

In this paper, we propose a people counting method based on fingerprinting localization. Traditional fingerprinting [10,11] consists of two phases: the offline training phase and online positioning phase. In the offline phase, received signal strength (RSS) and coordinates at predefined reference points are measured and stored in the database. In the online phase, location is estimated by comparing the measured RSS values with the pre-stored fingerprints. Typical algorithms like nearest neighbor (NN), k-nearest neighbor (KNN) and Bayesian algorithms are widely used for localization. This study utilizes the DIFF [12] method which considers signal strength differences between pairs of APs to process RSS values for reducing fingerprint differences caused by heterogeneous devices. Then KFCM clustering algorithm is adopted to divide the environmental region into different subareas to reduce the complexity and improve the efficiency. The people counting system can estimate the target location as well as the subarea it belongs to, and count the number of people for each subarea in real time.

The rest of the paper is organized as follows: Section 2 describes our proposed approach in detail. Several experiments have been conducted in section 3 for performance evaluation. Finally, the work is concluded in section 4.

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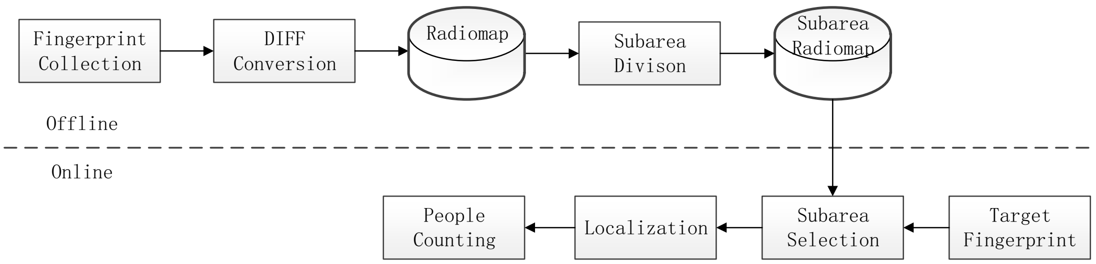


Figure 1. People counting model

II. METHODOLOGY

As illustrated in Fig. 1, our proposed approach consists of offline and online phases. The offline phase includes fingerprint collection, DIFF radiomap construction and subarea division. The online phase contains RSS collection, subarea selection, localization and people counting.

In the offline phase, we first measure RSS values between mobile devices and APs at the predefined reference points. The coordinates and RSS values at reference points constitute the radiomap. Then each fingerprint is transformed utilizing DIFF method to form the DIFF radiomap. Finally, we divide the fingerprint database into different clusters via KFCM clustering algorithm.

In the online phase, RSS values of the target are measured and transformed using DIFF method. Then, we determine which subarea the target belongs to. Next we estimate its location through typical algorithms such as KNN, Bayesian and Fuzzy. The estimated location is compared with the boundaries of all subareas, and then the region where the target is located can be determined. At last, we count the number of people in each region.

The main work of people counting are described in the following.

A. DIFF Radiomap Construction

In order to ensure accuracy, the fingerprints data in the offline and online phases must be consistent. Due to differences in hardware and antenna, different mobile devices may obtain different RSS values of the same AP even at the same location and time. RSS differences caused by device diversity at offline and online phases will undermine the consistency and lead to error.

We utilize DIFF method which is based on differential fingerprints to solve the signal strength variance problem between diverse devices. Signal strength differences between pairs of APs are used instead of the original RSS values.

Suppose there are *n* reference points and *m* available APs in the experimental environment. The space *L* can be denoted as a set of reference points with coordinates:

$$L = \{l_1 = (x_1, y_1), l_2 = (x_2, y_2), \dots, l_n = (x_n, y_n)\} \quad (1)$$

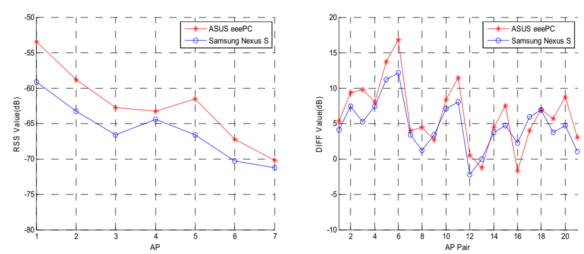
A fingerprint $r_{ij} = (r_{i1}, r_{i2}, \dots, r_{im})$ related to location l_i is a vector of RSS sample and r_{ij} denotes the RSS value from the *j*-th AP.

The DIFF method considers the differences between all possible pairwise AP combinations, thus the transformed fingerprints contain $C_m^2 = \frac{m(m-1)}{2}$ RSS differences. In this sense, the DIFF fingerprint is defined as

$$D(r_{ij}) = \{d(r_{i1}, r_{i2}), d(r_{i1}, r_{i3}), \dots, d(r_{i(m-1)}, r_{im})\} \quad (2)$$

Where $d(r_{ij}, r_{ik}) = r_{ij} - r_{ik}, 1 \le j < k \le m$ denotes the RSS differences between the *j*-th and *k*-th APs associated with location l_i.

RSS values collected at the same time and location with two different devices are shown in Fig. 2(a), and the values after DIFF conversion are shown in Fig. 2(b). It can be observed that DIFF values of the two devices are more consistent than the original RSS values. In this method, the fingerprints differences caused by device diversity are reduced. The radiomap constructed by DIFF fingerprints is applicable for heterogeneous devices.



(a) RSS values (b) DIFF values

Figure 2. RSS and DIFF values comparison at the same time and location with two different devices

B. Subarea Division Based on KFCM Algorithm

As concrete often causes radio attenuation, fingerprints collected in the same subarea are much more similar. We divide the indoor environment into subareas according to indoor structures such as rooms and corridors for reducing the computational complexity and improving the accuracy.

Suppose there are *n* reference points and *m* available APs in the experimental region. In the offline phase, we collect signal strength from APs at each reference point as well as the coordinates $l_i = (x_i, y_i)$, then the fingerprint database is defined as

$$FD = \{(r_{ij}, l_i) | 1 \le i \le n, 1 \le j \le m\} \quad (3)$$

After DIFF conversion, the fingerprint database is represented as

$$FD^* = \{(D(r_{ij}), l_i) | 1 \le i \le n, 1 \le j \le m\} \quad (4)$$

FD^* is divided into several clusters via KFCM clustering algorithm, where each cluster represents a subarea. KFCM algorithm is an improved method based on fuzzy c-means (FCM) algorithm. The kernel function maps the data from the original feature space to high dimensional space, where the RSS vectors become linearly separable.

The objective function of the KFCM algorithm is

$$J_m(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \|\phi(x_k) - \phi(v_i)\|^2 \quad (5)$$

In equation (5), n is the number of samples, $c(2 \le c \le n)$ is the number of clusters. U is the membership degree matrix, and V is the cluster center matrix. m is a weighting exponent. u_{ik} represents the membership degree of x_k belonging to the i-th cluster. $\phi(x_k)$ and $\phi(v_i)$ represent the vector of sample x_k and cluster center v_i mapped to high dimensional space respectively. $\|\phi(x_k) - \phi(v_i)\|$ represents the Euclidean distance.

Gauss kernel function is defined as

$$K(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \quad (6)$$

The detailed steps of KFCM clustering are as follows:

1) Initialize the parameter of Gauss kernel function δ, the number of clusters c, weighting exponent m, terminative precision ε, iterative counter t and cluster center v_i.

2) The membership degree matrix U is updated by

$$u_{ik} = \frac{\left(K(x_k,x_k)+K(v_i,v_i)-2K(x_k,v_i)\right)^{-\frac{1}{m-1}}}{\sum_{j=1}^{c}\left(K(x_k,x_k)+K(v_j,v_j)-2K(x_k,v_j)\right)^{-\frac{1}{m-1}}} \quad (7)$$

3) The cluster center matrix V is updated by

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^m K(x_k,v_i) x_k}{\sum_{k=1}^{n} u_{ik}^m K(x_k,v_i)} \quad (8)$$

4) If $\left|J^{(t+1)} - J^{(t)}\right| \le \varepsilon$, the iteration is stopped. Otherwise, increment t by 1 and return to step (2).

In equation (7) and (8), x_k is replaced by $FD_k^*(1 \le k \le n)$ that represents vectors in FD^*. After iterations, each sample belongs to the cluster that has the maximal membership degree.

$$Cluster_i = \{FD_k^* | max(U_{ik}), 1 \le i \le c, 1 \le k \le n\} \quad (9)$$

Through the above steps, FD^* is divided into different subareas to form radiomaps for multiple subareas. Fingerprints in the same subarea have high similarity.

C. Localization and People Counting

In the online phase, we first utilize NN algorithm to match the real-time measured RSS samples with each cluster center to select the nearest subarea. Suppose that the cluster centers are $v_i(i = 1,2,\ldots,c)$, the measured RSS sample is $s = (s_1, s_2, \ldots, s_m)$, and the Euclidean distance between cluster centers and RSS sample is represented as

$$ED(v_i, s) = \|v_i - s\| = \sqrt{\sum_{j=1}^{m}\left(v_{ij} - s_j\right)^2} \quad (10)$$

We select the cluster C_i with $\min(ED(v_i, s))$ as the subarea of the measured RSS sample. After the subarea of the target is determined, we utilize KNN algorithm as the matching algorithm to calculate its location. The distance between fingerprints in the database and measured RSS sample is represented as

$$ED\left(D(r_{ij}), D(s)\right) = \sqrt{\sum_{k=2}^{m} \sum_{j=1}^{m-1} \left(d(r_{ij}, r_{ik}) - d(s_j, s_k)\right)^2} \quad (11)$$

where $D(r_{ij})$ represents DIFF values of r_{ij} in $cluster_i$, and $D(s)$ represents DIFF values of s. We arrange $ED\left(D(r_{ij}), D(s)\right)$ in ascending order, and the top k reference points are selected. In this study, we set the value of k to 3. The location of the target is represented as

$$(\hat{x}, \hat{y}) = \frac{1}{k} \sum_{i=1}^{k} (x_i, y_i) \quad (12)$$

After the location of the target is determined, it is compared with the boundaries of all subareas. If the estimated location is within a subarea, then the subarea is determined. When applied to multiple targets, we can get locations of targets as well as the number of targets within each subarea.

III. PERFORMANCE EVALUATION

In this section, we conduct several experiments to validate the proposed approach. People counting accuracy, which refers to the number of people estimated accurately in subarea level, is used as the performance evaluation indicator and it is defined as

$$Accuracy = \frac{T}{N} \quad (13)$$

where T represents the number of test samples which are accurately estimated at subarea level, and N represents the total number of test samples.

A. Experimental Environment

The experimental test-bed is deployed on the fifth floor of the academic building with an area of approximately 860 m^2 [13]. The test-bed contains eight classrooms, four offices and a corridor. There are 5 APs deployed in the experimental region. Each reference point can receive signals from APs on the current floor and adjacent floors. Fig. 3 shows the layout of the experimental region with APs, reference points, room and corridor numbers denoted. A total of 82 reference points are defined in the area.

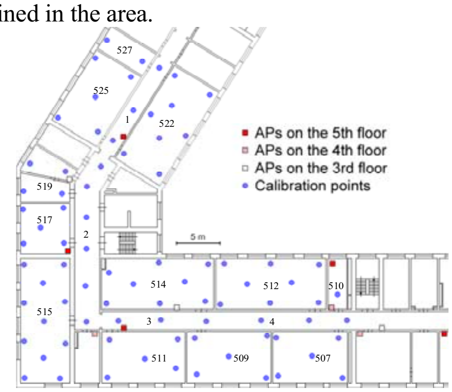
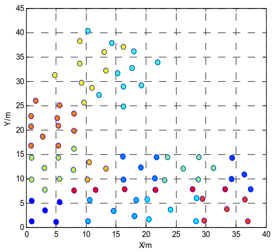


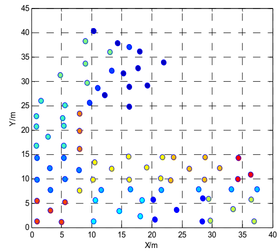
Figure 3. Layout of experiment context

B. Effect of Cluster Numbers

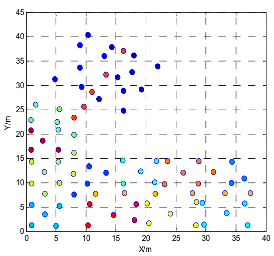
According to the layout, the experimental environment can be divided into 13-16 subareas. Fig. 4 shows the division of 13-16 clusters with KFCM clustering, and Table. I displays the average accuracy of different clusters.



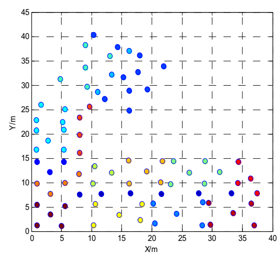
(a) C=13



(b) C=14



(c) C=15



(d) C=16

Figure 4. Division of 13-16 clusters

TABLE I. PEOPLE COUNTING ACCURACY WITH 13-16 CLUSTERS

Clusters	13	14	15	16
Accuracy (%)	86.91	90.24	87.21	88.66

It can be seen that the division of 14 clusters has the highest accuracy, and the division effect is more similar to the layout than the others compared with Fig. 3. Therefore, we discuss the performance of 14 clusters in the following subsections.

C. Effect of Parameter δ in Gauss Kernel Function

The value of parameter δ affects the performance of Gauss kernel function, and further affects the accuracy of localization and people counting. If δ tends to 0, all the samples support the vector; if δ tends to infinity, all the samples are classified as the same cluster. In this study, we select the values of [10,50] in steps of 5 to conduct multiple experiments and the results are shown in Fig. 5. It can be seen that the proposed approach has the best performance when δ is set to 30.

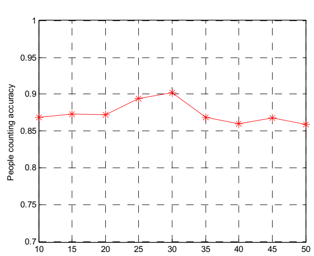
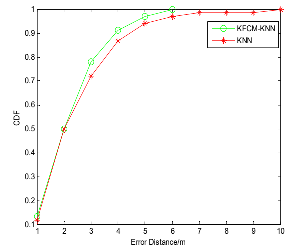


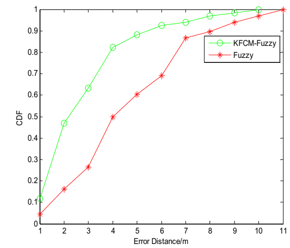
Figure 5. People counting accuracy influenced by the value of δ

D. Localization Error with Subarea Division

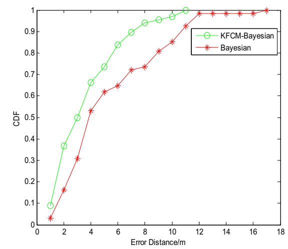
We randomly select 34 test points distributed in different subareas to conduct the experiments. At each point, we collect the RSS samples twice, so there are a total of 68 samples. Location estimation is performed through KNN, Fuzzy and Bayesian algorithms. We calculate the location in two ways, one of which includes subarea division and the other not. The performance of different algorithms are compared in Fig. 6.



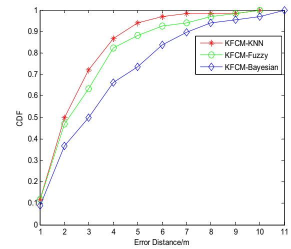
(a) KNN



(b) Fuzzy



(c) Bayesian



(d) KNN, Fuzzy, Bayesian

Figure 6. The cumulative distribution function (CDF) of error distance. (a) CDF of KFCM-KNN and KNN. (b) CDF of KFCM-Fuzzy and Fuzzy. (c) CDF of KFCM-Bayesian and Bayesian. (d) CDF of KFCM-KNN, KFCM-Fuzzy and KFCM-Bayesian.

We can see from Fig. 6(a) – Fig. 6(c) that subarea division can improve the accuracy of localization. The CDF of the three algorithms is compared in Fig. 6(d), which indicates that the performance of KFCM-KNN is better than the other two algorithms in our experiments.

The localization errors between actual locations and estimated locations are shown in Fig. 7, and the average error is 2.58m.

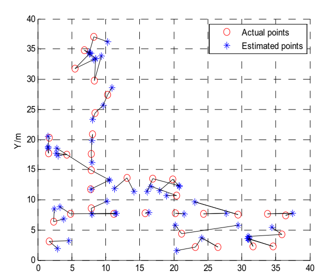


Figure 7. Errors between actual locations and estimated locations

E. People Counting Result

We show the people counting result at subarea level in Table. II. In the table, actual number of samples refers to the number of samples collected during the online phase.

Estimated number of samples means the number of samples obtained by our proposed approach. It may contain some erroneous results. Correct number of samples indicates the number of samples estimated correctly at subarea level. As a result, 61 out of 68 samples are estimated precisely at subarea level.

TABLE II. PEOPLE COUNTING RESULT OF AN EXPERIMENT AT SUBAREA LEVEL

Room/ corridor#	Actual number of samples	Estimated number of samples	Correct number of samples
R507#	6	6	6
R509#	6	9	6
R514#	8	11	8
R515#	6	6	6
R517#	6	6	6
R525#	8	8	8
C1#	2	3	2
C2#	10	8	8
C3#	8	4	4
C4#	8	7	7

Several experiments have been conducted and the people counting accuracy of our proposed method is shown in Table. III. The worst accuracy is 85.29%, the best accuracy is 95.59% and the mean accuracy is 90.24%.

TABLE III. PEOPLE COUNTING ACCURACY AT SUBAREA LEVEL

Worst (%)	Best (%)	Mean (%)
85.29	95.59	90.24

On the whole, the above experimental results show that our proposed people counting approach has the potential to be applied in practice.

IV. CONCLUSION

In this study, we present a method for counting the number of people within a region based on indoor fingerprinting localization. The proposed approach consists of offline phase and online phase, the most important of which are DIFF radiomap construction and KFCM clustering. In offline phase, we measure fingerprints and construct the radiomap, which is then transformed using DIFF method to solve the problem of device diversity. Next we divide the whole region into different subareas utilizing KFCM Clustering algorithm to reduce the computational complexity. In online phase, we first select the nearest subarea of the target with NN algorithm and estimate its location with KNN algorithm. The target location is compared with the boundaries of all subareas for the determination of the target subarea. When applied to multiple targets, the number of people in each subarea will be counted. Experimental results show that the proposed method is capable of reporting the number of people at subarea level.

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REFERENCES

[1] K.Y. Yam, W. C. Siu, N. F. Law et al., "Effective bi-directional people flow counting for real time surveillance system," IEEE International Conference on Consumer Electronics, vol. 10, no. 11, pp. 863-864, 2011.

[2] H. Xu, P. Lv and L. Meng, "A People Counting System based on Head-shoulder Detection and Tracking in Surveillance Video," IEEE International Conference on Computer Design and Applications, pp. 394-398, 2010.

[3] H. Han, B. Sheng, C. C. Tan et al., "Counting RFID tags efficiently and anonymously," in Proceedings IEEE INFOCOM, pp. 1–9, 2010.

[4] N. Li, G. Calis, B. Becerik-Gerber, "Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations," Automation in Construction, vol. 24, no. 2, pp. 89-99, 2012.

[5] H. Li, E. C. L. Chan, X. Guo et al., "Wi-counter: Smartphone-based people counter using crowdsourced Wi-Fi signal data," IEEE Transactions on Human-Machine Systems, vol. 45, no. 4, pp. 442–452, 2015.

[6] S. D. Domenico, M. D. Sanctis, E. Cianca et al., "A trained-once crowd counting method using differential wifi channel state information," in Proceedings of the 3rd International on Workshop on Physical Analytics, pp. 37-42, 2016.

[7] N. Ahmed, A. Ghose, A. K. Agrawal et al., "SmartEvacTrak: A people counting and coarse-level localization solution for efficient evacuation of large buildings," IEEE International Conference on Pervasive Computing and Communication Workshops, pp. 372-377, 2015.

[8] C. Xu, B. Firner, R. S. Moore et al., "SCPL: Indoor device-free multi-subject counting and localization using radio signal strength," ACM/IEEE International Conference on Information Processing in Sensor Networks, pp. 79-90, 2014.

[9] W. Xi, J. Zhao, X. Y. Li et al., "Electronic frog eye: Counting crowd using WiFi," in Proceedings IEEE INFOCOM, pp. 361–369, 2014.

[10] M. Zhou, F. Qiu, Z. Tian et al., "An information-based approach to precision analysis of indoor WLAN localization using location fingerprint," Entropy, vol.17, no. 12, pp. 8031-8055, 2015.

[11] S. He, 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, 2017.

[12] C. Laoudias, D. Zeinalipour-Yazti, C. G. Panayiotou. "Crowdsourced indoor localization for diverse devices through radiomap fusion," Macromolecules, vol.35, no. 12, pp. 4628-4635, 2013.

[13] G. Jekabsons, V. Zuravlyov, "Refining Wi-Fi based indoor positioning," in Proceedings of 4th international scientific conference applied information and communication technologies, pp. 87-95, 2010.