On the Pedestrian Flow Analysis Through Passive WiFi Sensing

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***Abstract*—The proliferation of mobile devices, including smartphones and tablets, has been enabling new possibilities for inferring information about the positions, behavior and activities of the users carrying these devices. For instance, by leveraging the WiFi probes sent out by mobile devices in public spaces (such as shopping malls, metro stations, etc.), even if pedestrians do not have their mobile devices to be associated with any WiFi access point (AP), it is attractive to conduct pedestrian analysis in a passive sensing approach to facilitate the efficient management of public infrastructures as well as convenient customer services. This paper considers the problem of pedestrian flow analysis by implementing a pedestrian surveillance system in the transfer channel of a metro station in Guangzhou China. Firstly, a fingerprint database is generated through a Gaussian process regression (GPR) approach. On these grounds, a pedestrian number estimation method based on linear regression is presented by making use of the fingerprint-based localization method to refine the number of mobile devices residing in the surveillance area, and a pedestrian velocity estimation method is proposed based on particle filter and the inverse distance weighted (IDW) method. According to the dataset obtained in real scenarios, the effectiveness and advantages of the proposed two methods are confirmed.**

***Index Terms*—WiFi sniffing, pedestrian number estimation, velocity estimation, passive sensing, crowdsourcing**

I. Introduction

Nowadays, WiFi network infrastructures (e.g. WiFi access points (APs)) and WiFi enabled mobile devices (e.g. smartphones and tablets) have become pervasive in our daily lives. In light of IEEE 802.11 Standard, a mobile device actively and periodically sends out probe (request) frames across different channels for the purposes of associating with an AP or switching between different APs; correspondingly, any AP in the vicinity of this mobile device might receive such a probe frame irrespective of whether the mobile device is associated with it, and normally returns a probe response frame. Since the probe frames involve spatial-temporal information about the user carrying this mobile device, a special kind of WiFi APs, termed WiFi sniffers, can thus be leveraged to passively sense users' behavior and activities in public spaces [1], such as shopping malls, metro stations, etc., through crowdsourcing the probe frames from their mobile devices, enabling new possibilities for developing various novel applications in an automatic and non-intrusive way, such as pedestrian flow or crowd analysis [2]–[5], tracking trajectories [6], unveiling social relationship [7]–[10], measuring queueing time [11], localization [12], [13], understanding urban scenes [14]–[16], etc. In fact, besides probe frames, WiFi sniffers are able to receive normal WiFi packets, so as to further enhance their sensing capability.

In public spaces with massive pedestrian traffics, such as metro transfer channels, underground pedestrian passages, and so on, it is of great importance to monitor pedestrian situations in real time. However, the popular video based approaches suffer from low performance due to poor illuminations, high crowd densities and high computational complexities [17], and thus, leveraging WiFi sniffers for pedestrian flow analysis becomes attractive in the literature.

Firstly, learning the number of pedestrians residing in or passing through a specific region plays vital role in understanding the criticality of a situation [18]. In [2], a motion sensor was employed to collect ground-truth of the number of pedestrians entering a shopping mall, such that one slope coefficient was trained to map the number of MACs detected by WiFi sniffers to the pedestrian number; the field experiments showed that, this method does not work when the number of MACs is below say 2000, and suffers higher error rates than 30% when the number of MACs is around 2000. In [3], WiFi

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sniffers with directional antennas were adopted to provide more accurate positional information of detected mobile devices, with the result that the resulting error rates can be less than 20%. In [5], a stereoscopic camera was installed at a specified calibration choke point to collect the ground-truth of pedestrian numbers, so as to reduce the error rates below 20%. Therefore, great efforts have to be made in order to achieve more accurate estimates of pedestrian numbers.

Secondly, since simply using pedestrian numbers does not allow for a complete assessment of the criticality of a situation, knowing pedestrian velocities is also a key factor for the dynamic management of public infrastructures as well as providing convenient customer services [19]. In [20], pedestrians share their position information determined by GPS through an APP installed on their smartphones, such that pedestrian velocities can be directly inferred, which does not belong to the passive sensing approach considered in this paper. Intuitively, estimating a pedestrian velocity through WiFi sniffers demands detecting a mobile device carried by the pedestrian at least twice so as to determine a physical distance and a corresponding time interval. The most popular WiFi fingerprint-based localization method [21] can thus be employed for calculating such distances, but is inevitably degraded in the considered situation due to severe dynamics and device heterogeneity, implying that it is challenging to carry out reliable pedestrian velocity estimation.

This paper investigates the above two problems occurring in pedestrian flow analysis through passive WiFi sensing. To this end, a pedestrian surveillance system consisting of 5 WiFi sniffers was installed at the transfer channel of the Yanji metro station in Guangzhou, China, and a sniffing dataset involving four typical scenarios was derived for further processing and analysis. In addition, a fingerprint database, produced by using the Gaussian process regression (GPR) method given received signal strength (RSS) measurements only at a limited number of reference points [22], [23], is employed to provide position information of mobile devices detected by the sniffers. On these grounds, a linear model is firstly regressed based on the least squares method for estimating pedestrian numbers by making use of localized mobile devices; then, particle filter is adopted to estimate pedestrian velocities based on the inverse distance weighted (IDW) method given a sequence of RSS measurements which can be crowdsourced by sniffers. Performance evaluations are carried out and validate the feasibility and effectiveness of the proposed two methods. It is shown that both of the methods are able to deliver the estimation accuracy of around 10%, which is significantly better than existing other approaches.

The rest of the paper is organized as follows. Section II provides an overview of the proposed surveillance system. Section III and Section IV respectively introduce the pedestrian number and velocity estimation methods and corresponding experimental results. We conclude this paper in Section V.

II. Overview of the Pedestrian Surveillance System

In this section, we first briefly introduce the pedestrian surveillance system, and then present an overview of the sniffing dataset.

A. System Overview

The pedestrian surveillance system was deployed at the transfer channel between Line 1 and Line 5 in the Yangji metro station in Guangzhou, China, and consisted of five WiFi sniffers. Specifically, four of them were installed at the four corners of the surveillance area, i.e. a rectangle with the length of 16.9 meters and width of 5.22 meters, and the other one at the center. The surveillance area is separated into two lanes by using fixed fences, such that the pedestrian flow is bidirectional.

All the WiFi sniffers and a server were connected to a 100 Mbps switch to form a wired local area network. A UDP server program was developed and installed on the server to collect data, including MAC address, RSS, time stamps and channel ID, which were uploaded by each WiFi sniffer at the frequency of 10 Hz.

B. WiFi Sniffers

The pedestrian surveillance system employed customized WiFi sniffers (i.e. *DS-AP-I* [24]), each of which integrates nine dual-band WiFi modules and is thus able to simultaneously sniff nine different channels, with the result that more mobile devices and more WiFi packets (including both probe requests and normal data packet) can be crowdsourced in comparison with standard WiFi sniffers with only one dual-band WiFi module.

In particular, five modules were scheduled to work in 2.4 GHz with each one polling three of 13 channels, and similarly, four modules in 5.8 GHz with each one polling two of 12 channels. In addition, during channel polling, each module kept sniffing one channel for 300 milliseconds. Note that one channel might be polled by two different modules.

C. Fingerprint Database

A fingerprint database was established through an offline site survey process to enable WiFi fingerprint-based localization. In order to determine whether a mobile device is located inside of the surveillance area, the fingerprint database involves 76 reference points in the surveillance area and another 99 reference points in the neighboring non-surveillance area.

To reduce the workload required in the offline site survey, the GPR based approach reported in [22], [23] was adopted to produce a fingerprint database by collecting RSS measurements through an Android smartphone (Huawei Honor 6) and an iOS smartphone (Iphone 7) from only 25% of the reference points. To disentangle the complexity introduced by different frequencies, we only establish the fingerprint database by using the RSS measurements in 2.4 GHz.

TABLE I
THE DETAILS OF THE SNIFFING DATASET IN FOUR TYPICAL SCENARIOS.

Description	Date	Start Time	End Time	Duration	Number of Packets	Number of MACs
Evening Peak	Dec 26, 2018 (Wed)	17:47:51	18:45:46	57min 55sec	13714275	58940
Evening Off Peak	Dec 26, 2018 (Wed)	21:34:55	22:20:26	45min 31sec	6325523	16580
Morning Peak	Dec 27, 2018 (Thur)	07:48:23	08:52:12	63min 49sec	14105625	54101
Afternoon Off Peak	Dec 27, 2018 (Thur)	13:00:02	13:46:44	46min 42sec	5780439	21678

D. Sniffing Dataset

Sniffing data were collected in four typical scenarios during two work days, namely evening peak, evening off peak, morning peak and afternoon off peak, as shown in Tab. II-D. It can be observed that, more than thirteen millions packets were sniffed in the peak times by the five sniffers, and around six millions packets in the off peak times; in terms of independent MACs, more than fifty thousands MACs were detected in the peak times, whereas only around twenty thousands MACs in the off peak times. Therefore, such an abundant of information enables us to carry out advanced pedestrian flow analysis.

III. ESTIMATING THE PEDESTRIAN NUMBER

In this section, we first elaborate the design of the proposed pedestrian number estimation method, and then report experimental results for performance evaluation.

A. Method

In the literature [2], [3], [5], linear regression is commonly adopted to learn the relationship between the number of MACs detected and the number of pedestrians. However, our study differs from the existing studies in the following three aspects. First, unlike the existing studies only using one coefficient (i.e. slope), the proposed method learns a linear model with two coefficients (i.e. slope and intercept) because intercept helps to alleviate the influence of fixed devices existing in the surveillance area. Second, the proposed method excludes the mobile devices that lie outside of the surveillance area based on the WiFi fingerprint-based localization method, so as to improve the reliability and accuracy of the sniffing data fed into the linear model. As a result, it is unnecessary to preprocess sniffing data to remove the MACs in relation to fixed devices and passer-by devices as was done in [2]. Third, since metro management demands low latency, the estimation method is implemented in a small time granularity, namely that the numbers of MACs detected are calculated every minute, such that the resulting pedestrian number estimate is produced every minute, whereas the existing works only considered hourly or longer results.

Furthermore, the least squares method is applied to formulate the linear regression problem, and the k nearest neighbor (kNN) method is adopted to calculate the final localization result in the WiFi fingerprint-based localization technique. One mobile device can be localized as long as the number of sniffers detecting it exceeds a predefined minimal number (say 1, 3 or 4), and is accepted for further processing only if the localization result lies inside of the surveillance area. Note that RSS measurements obtained by one same sniffer during one second are averaged for use in localization.

B. Performance Evaluation

In order to validate the effectiveness of the proposed method, we first trained two regression models without using localization: the first one was trained by using the MACs detected by NO.3 sniffer which was installed in the center of the surveillance area, and the second one by using the MACs detected by any of the five sniffers. Moreover, we took into account different values taken by two key parameters m (i.e. the minimal number of RSS measurements) and k in KNN in the localization procedure to understand their influences.

As the beginning of our study, this study utilized a video camera installed at one end of the transfer tunnel to record pedestrian flows for around 15 minutes in each typical scenario, such that the pedestrian numbers were manually counted in an offline manner as the ground-truth. As a result, we obtained 67 samples for both training and testing purposes, each of which includes the number of MACs detected to lie inside of the surveillance area and the corresponding pedestrian number in one minute. The training samples and testing samples were randomly determined according to five-fold cross validation.

The RMSE and normalized RMSE (NRMSE) are listed in Tab. II and Tab. III, respectively, where NRMSE is defined as [5]

$$\frac{RMSE}{\max_t g_t - \min_t g_t} \times 100\% \tag{1}$$

with g_t denoting the ground-truth of the pedestrian number in the t-th testing sample.

It is evident that the proposed method using localization results significantly outperforms the method without using localization by around 30%, while the two implementations of the latter do not have evident difference, implying that the number of sniffers does not affect the performance of the latter. Furthermore, it can be observed that the performance of the proposed method slightly improves with m and k increasing, which is contributable to the fact that the localization accuracy also increases with m and k increasing.

In order to have a clear observation, one set of linear regression models was randomly selected from the five-fold cross validation sets, as plotted in Fig. 1. It can be seen that, the training samples (i.e. the scattered circles, diamonds or squares in Fig. 1) in the proposed method are more concentrated to the corresponding regressed straight lines than those without using localization, which is consistent with the results in Tab. II and Tab. III.

TABLE II
RMSE USING FIVE-FOLD CROSS VALIDATION.

NO.	NO.3 Sniffer	All Sniffers	$m > 1$			$m > 2$			$m > 3$		
			$k = 6$	$k = 4$	$k = 1$	$k = 6$	$k = 4$	$k = 1$	$k = 6$	$k = 4$	$k = 1$
1	28.24	33.63	23.27	20.99	18.38	24.14	22.70	19.12	24.95	24.46	20.31
2	36.79	30.61	27.37	27.81	27.98	25.13	23.72	25.90	25.59	24.03	23.32
3	43.61	40.45	32.38	33.86	33.80	35.53	37.10	33.68	34.52	34.72	33.73
4	43.96	44.37	34.35	34.06	31.19	33.51	32.74	30.60	33.68	32.17	30.67
5	37.29	39.85	29.95	29.84	25.38	31.68	32.87	29.79	33.40	34.07	33.20
Average	37.97	37.78	29.46	29.31	27.34	30.00	29.83	27.82	30.43	29.89	28.25

TABLE III
NRMSE USING FIVE-FOLD CROSS VALIDATION.

NO.	NO.3 Sniffer	All Sniffers	$m > 1$			$m > 2$			$m > 3$		
			$k = 6$	$k = 4$	$k = 1$	$k = 6$	$k = 4$	$k = 1$	$k = 6$	$k = 4$	$k = 1$
1	11.09	13.21	9.13	8.24	7.22	9.48	8.91	7.51	9.80	9.61	7.97
2	17.11	14.26	12.79	12.99	13.08	11.74	11.08	12.12	11.97	11.24	10.92
3	14.44	13.43	10.75	11.24	11.20	11.80	12.32	11.18	11.46	11.52	11.20
4	15.32	15.49	11.98	11.87	10.86	11.66	11.41	10.65	11.74	11.23	10.71
5	12.70	13.68	10.28	10.23	8.69	10.93	11.34	10.26	11.52	11.74	11.46
Average	14.13	14.01	10.98	10.91	10.21	11.12	11.01	10.34	11.30	11.07	10.45

IV. ESTIMATING THE PEDESTRIAN VELOCITY

In this section, we first present a sniffing dataset analysis to demonstrate the feasibility of estimating pedestrian velocities through a passive approach, then describe a particle filter based method, and finally report the experimental results.

A. Analysis of Sniffing Dataset

Since estimating the velocity of a pedestrian carrying a mobile device requires localizing the mobile device at least twice, it is necessary to investigate whether this condition can be satisfied in the pedestrian surveillance system. To this end, we summarize the frequency (i.e. the number) of mobile devices that can be localized between 4 and 20 times, as illustrated in Fig. 2. The event that a mobile device can be localized l times means that l sets of RSS measurements are available with the minimal time interval between any two sets greater than or equal to 1 second. It can be observed that around 10% of the total MACs in each typical scenario can be localized between 4 and 20 times, which is sufficient for us to carry out pedestrian velocity estimation. As a result, it is feasible to further infer pedestrian flow velocities based on these individual estimates.

B. The Particle Filter based Method

In what follows, we shall present the particle filter based method for estimating the velocity of an individual pedestrian and leave the study of pedestrian flow velocity in our future works.

Let the state of the i-th particle at t-th time instance with $i = 1, 2, \cdots$ and $t = 1, 2, \cdots$ include the two-dimensional position, denoted $\mathbf{x}_t^i$, where a mobile device is initially detected, and its velocity v_t^i. Since the surveillance area is a transfer channel, each pedestrian can be assumed to *walk at a constant velocity along a horizontal straight line*, which is parallel with the side of the transfer channel. As such, we can establish the following state space model

$$\begin{bmatrix} \mathbf{x}_t^i \\ v_t^i \end{bmatrix} = \begin{bmatrix} \mathbf{x}_{t-1}^i \\ v_{t-1}^i \end{bmatrix}. \tag{2}$$

Given the RSS measurement vector obtained by the five sniffers at time instance t, denoted $\mathbf{r}_t$, the weight associated with the i-th particle is updated as follows

$$w_t^i = w_{t-1}^i \times \Pr(\mathbf{r}_t | \mathbf{x}_t^i + \begin{bmatrix} v_t^i & 0 \end{bmatrix}^T \times (T_t - T_1)), \tag{3}$$

where $\Pr(\cdot|\cdot)$ computes the probability of a given RSS measurement vector conditional on a given position, and T_t denotes the real time in second at the t-th time instance.

However, the fingerprint database only involves the fingerprints at a set of discrete reference points, which often do not include a given position. Therefore, we adopt the IDW method to interpolate the mean and standard deviation of a RSS measurement vector at the given position by using the 4 nearest neighboring reference points, so that the probability in (3) can be calculated by assuming that the RSS measurement vector $\mathbf{r}_t$ satisfies a joint independent Gaussian distribution with the interpolated mean and standard deviation.

When initializing particles, their positions are drawn from the reference points according to a two-dimensional Gaussian distribution with the mean value at the initial localization result and standard deviation of $3\mathbf{I}$ (where $\mathbf{I}$ is an identity matrix of order 2), and their velocities from $[0.4, 1.4$ according to a uniform and random distribution. Finally, the weighted mean value of the velocities among all the particles is returned as the velocity estimate.

C. Performance Evaluation

To validate the performance of the pedestrian velocity estimation method, one female experimenter was asked to carry an iOS smartphone (Iphone 6S) and walk four times through the transfer channel by following crowds from both directions in each typical scenario. Meanwhile, the times when the experimenter entered and exited the

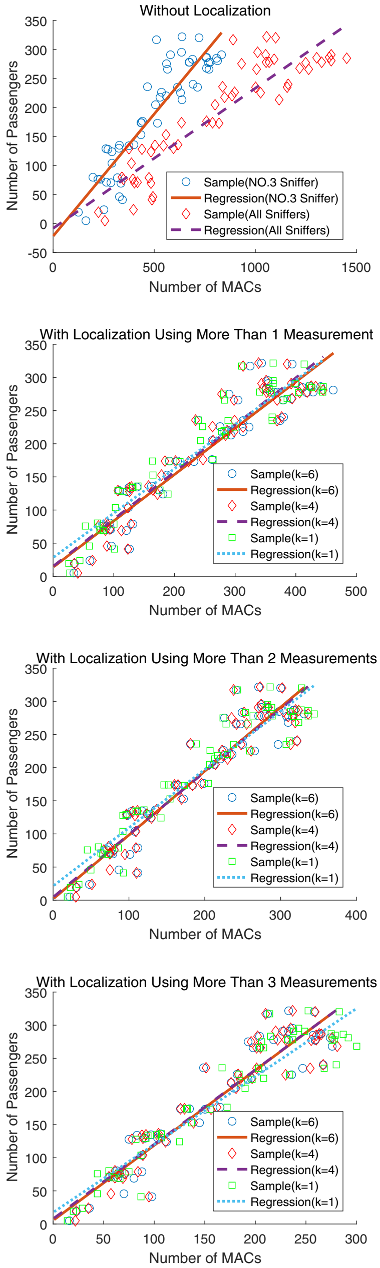

Fig. 1. Frequencies with respect to sampling times (starting from 4) of same MAC in different data sets.

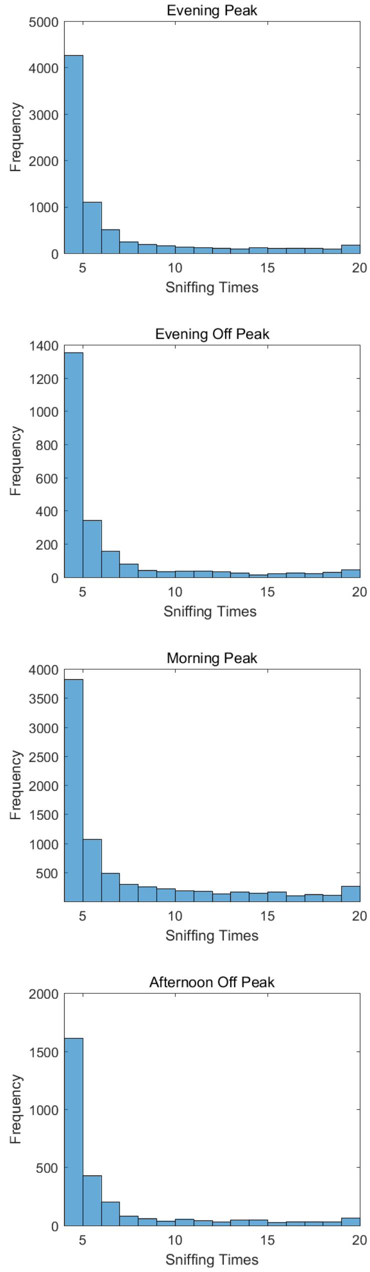

Fig. 2. Frequencies with respect to sampling times (starting from 4) of same MAC in different data sets.

surveillance area were also recorded, for the purpose of obtaining the ground-truth of her velocities. To avoid the issues of MAC randomization and less than 2 localization times, the smartphone was associated with a WiFi AP and the experimenter kept refreshing the WiFi list.

The particle number n is set to be 1000 in the experiment, and the error rate of the proposed velocity estimation method is defined to be

$$\frac{\text{abs}(v - \hat{v})}{v} \times 100\% \tag{4}$$

where v and $\hat{v}$ denote the true and estimated velocities, respectively.

The experimental results with respect to four typical scenarios are listed in Tab. IV-C. As can be seen, the average error rates fluctuate around 10%, which is acceptable for management purposes. However, there do exist several outliers with the error rates above 30%. This issue can be mitigated in further pedestrian flow velocity estimation, due to the fact that more pedestrians will be involved in velocity estimation and the outliers can be averaged out.

V. Conclusion

In this paper, we introduced the pedestrian surveillance system in the metro transfer channel through passive WiFi sensing. Firstly, the pedestrian number estimation method was reported based on linear regression by making use of the fingerprint-based localization method to provide accurate numbers of MACs residing in the surveillance area. Secondly, the pedestrian velocity estimation method

TABLE IV
THE ERROR RATES OF THE PROPOSED VELOCITY ESTIMATION METHOD IN FOUR TYPICAL SCENARIOS. "RADB" MEANS THE A-TH ROUND AND THE B-TH DIRECTION.

Description	R1D1	R1D2	R2D1	R2D2	R3D1	R3D2	R4D1	R4D2	Average
Evening Peak	0.50	4.57	16.47	3.52	38.05	14.60	10.54	10.35	12.32
Evening Off Peak	3.54	2.05	6.05	11.19	12.89	41.98	0.35	1.45	9.94
Morning Peak	2.83	16.63	5.80	6.22	0.74	33.42	1.22	12.57	9.93
Afternoon Off Peak	3.29	5.03	3.84	33.01	6.34	6.87	14.67	6.96	10.00

was proposed based on particle filter and the IDW method. Based on the dataset crowdsourced during four typical scenarios, the feasibility and effectiveness of the proposed methods were demonstrated.

However, as the beginning of our study, there still exist several problems that shall be considered in our future works. First, we obtain the ground-truth of true pedestrian numbers in training the model by manually counting, and intend to adopt other sensory approaches to implement automatical and online training and calibration. Second, since the system was realized in a passive approach, device heterogeneity inevitably degraded the performance. Third, the proposed velocity estimation focuses on individual pedestrian, and will be extended to realize pedestrian flow velocity estimation. Fourth, more and more mobile devices are adopting MAC randomization for privacy protection, and thus it is necessary to evaluate the adaptability of the proposed methods in larger surveillance areas given random MACs. Last but not least, since signal attenuation in 2.4 GHz is quite different from that in 5.8 GHz, the resulting fingerprint database and localization algorithm need to be adapted to guarantee localization performance.

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