SCaNME: Location tracking system in large-scale campus Wi-Fi environment using unlabeled mobility map

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1. Introduction

Location tracking in wireless network has attracted significant interest in recent years. Knowledge of people’s real-time locations and related routine activities make many promising applications for industrial and public uses (Hornig, Ching, Ferng, Kao, & Li, 2011; Zhang, Liu, Jiang, & Guan, 2013) for childcare, elderly health care, emergency rescue, as well as management in warehouse and modern buildings (Cura, 2010; Dey et al., 2011). Moreover, by the year 2014, the GPS technology could yield more than 2.5 billion dollars device market and over 12.7 billion dollars are expected to be reported by location-based service (LBS) market at that time (Ashbrook & Starner, 2003).

GPS and the Cellular network are two established infrastructures for location tracking, but they cannot work well in some urban or indoor environments due to the poor quality of the received signal from satellites or base stations. Serious attenuation and multipath interference exists in challenging radio propagation environments, such as buildings, tunnels, and subway stations (Anisetti, Ardagna, Bellandi, Damiani, & Reale, 2011; Wong et al., 2009). Therefore, a large amount of effort has been made to track people’s locations by alternative technologies, including the radio frequency identification (RFID) (Silva & Goncalves, 2009), ultrasonic wave (UW) Yoshiga et al., 2012, ZigBee (Goncalo & Helena, 2009), Bluetooth (Mair & Mahmoud, 2012), ultra-wideband (UWB) Steiner & Wittneben, 2010, and infrared ray (IR) Chen et al., 2010. However, these technologies require additional costs of infrastructure and maintenance, great effort for fingerprint or landmark calibration, frequent signaling between the mobile users and infrastructure, and rigorous application scenarios.

Based on the previous work on the location tracking in Wi-Fi environments (Ouyang, Wong, Lea, & Chiang, 2012; Ouyang et al., 2010; Zhou, Tian, Xu, Yu, & Wu, 2013; Zhou et al., 2013), we can find that the Wi-Fi technology has the advantages of high accuracy, low cost, and widespread deployment. Moreover, the Wi-Fi modules can be integrated in most of current personal mobile devices, such as the laptops, cell phones, tablets, and personal digital assistants (PDAs). Therefore, after the world’s pioneering Wi-Fi location tracking system, RADAR, was invented by Microsoft Research in 2000 (Bahl & Padmanabhan, 2000), many universities and institutes began to develop a variety of prototype and commercial systems to track people’s locations (Castro et al., 2021; Garcia-Valverde et al., 2013; Swangmuang & Krishnamurthy, 2008; Youssef & Agrawala, 2008).

So far, there are generally four types of location tracking techniques by using the Wi-Fi networks: the time or time difference...
of arrival (TOA or TDOA) (Golden & Bateman, 2007; Schwalowsky et al., 2010), angle of arrival (AOA) (Wong et al., 2007, 2008), propagation model (Ahn & Yu, 2008; Emery & Denko, 2007), and received signal strength (RSS)-based fingerprinting (Bahl & Padmanabhan, 2000; Castro et al., 2002; Swangmuang & Krishnamurthy, 2008; Youssef & Agrawala, 2008). By TOA or TDOA, strict time synchronization of access points (APs) and mobile stations within a network is required (Golden & Bateman, 2007; Schwalowsky et al., 2010). However, multipath fading and shadowing in target environment make it difficult to obtain the exact arrival time of signal and propagation distance. In other words, the results of location tracking obtained by the combination of log-distance path loss model with triangulation algorithm cannot be accurate. For AOA technique, it is suggested that the smart antenna is used at the receiver to track locations by measuring the angles of arrival signal (Wong et al., 2007, 2008). In all, the TOA or TDOA and AOA techniques heavily rely on the sophisticated propagation model and extra hardware to achieve location tracking.

In comparison, the Wi-Fi RSS-based fingerprinting is preferred for location tracking because there is no requirement for any extra devices besides the widely deployed Wi-Fi networks in public. In general, there are two phases involved in the tracking process, the off-line phase and on-line phase (Fang & Lin, 2010; Zhou, Xu, Ma, & Tian, 2012). In the off-line phase, the fingerprints from the RSS measurements at reference points (RPs) and the corresponding physical coordinates are recorded to construct a radio map. Then, in the on-line phase, the people’s locations are estimated by matching the pre-stored fingerprints with the new RSS data. The major drawback of RSS-based fingerprinting is the intensive labor cost for the fingerprint calibration.

To solve this problem, we propose a novel location tracking system called ScaNME which can adaptively construct an unlabeled mobility map and track people’s locations and paths without any calibration of fingerprints. The research presented in this study is an extension of our previous work (Zhou et al., 2013). Different from the conventional radio map, the unlabeled mobility map is represented by a graph of RSS clusters associated with non-zero transition probabilities. Meanwhile, by using the Allen’s logics on the temporal relations of time stamped RSS clusters, the people’s activities can be recorded from the mobility map. In this paper, we mainly focus on the activity recording for the people from the same organization. Our proposed ScaNME is beneficial to the future user-centric ubiquitous LBS which requires not only the knowledge of people’s real-time location information, but also the understanding of people’s routine activities. In the environments where the people’s movement patterns have been recorded, we can use ScaNME for loss finding, such as Find my phone at phone. On the other hand, for healthcare applications, by tracking the movement of elderly people, the nursing center can monitor the activities of their care-receivers, or the families of the elder can track their locations anytime on-line in cloud. In all, the activity recording-based LBS could make our life easier and secure. Another application of ScaNME system is to describe the layout of anonymous environments adequately and adaptively. The off-line RSS training involved in conventional fingerprint-based location tracking systems requires significant time cost and periodic RSS management. To guarantee the efficiency of RSS training, a rough floor plan could be essential to the creation of off-line RSS database. However, in many anonymous environments, the floor plans are probably not available to the users for the security or privacy reasons. To solve this problem, the mobility map constructed by ScaNME system can be used to describe the target environmental layout in an effective manner. The ScaNME consists of the off-line map training phase and the on-line location tracking phase. The objectives of the off-line map training phase are to construct an unlabeled mobility map and record the people’s motion behaviors. During the on-line location tracking phase, the people’s locations and paths are tracked in a real-time manner.

The remaining of this paper is organized as follows. Section 2 summarizes some related work on Wi-Fi location tracking and describes the purpose of mobility map construction in ScaNME system. Section 3 explains the steps of tracking people’s locations by ScaNME system. In Section 4, we discuss the way to record the people’s activities from the unlabeled mobility map by Allen’s logics. Section 5 provides some numerical results collected from the experiments in a campus-wide Wi-Fi network. In Section 6, we conclude the paper and present our future work.

2. Related work

In the recent decade, the proliferation of ubiquitous LBS demand has fostered the research of Wi-Fi location tracking in both industry and academia. The fundamental model for the RSS-based location tracking was built by Microsoft Research’s RADAR system (Bahl & Padmanabhan, 2000). In RADAR system, the ideas of RSS-based fingerprinting and radio propagation model for the location tracking are introduced, which also become the two leading schemes to locate the people’s positions in Wi-Fi environments.

2.1. RSS fingerprint-based location tracking

Horus (Youssef & Agrawala, 2008) is another prominent location tracking system featured with high accuracy and low computation cost. As a probabilistic location system, Horus studied the problems including the RSS sequence correlation with different sample delays, relations of RSS mean and sample number, and variations of spatial characteristics with respect to the environmental changes. Castro and coauthors in Castro et al. (2003) developed another probabilistic location system called Nibble to infer the people’s positions by using the signal quality measurements. Both the Horus and Nibble systems rely on the Bayesian theory to realize the location tracking in Wi-Fi environments, but the major difference is about the way to describe the RSS distributions at RPs. The former one fits each RSS distribution as a Gaussian curve, whereas the latter one uses a histogram to depict the frequencies of RSS. In Swangmuang and Krishnamurthy (2008), Krishnamurthy applies proximity graphs to approximate the error distributions, and thereby tunes the fingerprint database. They also investigated the variations of RSS distributions with respect to the body shadowing and device orientation changes, as discussed in Kaemarungsi and Krishnamurthy (2004). In general, these results can help to better understand the variation properties of RSS fingerprints in Wi-Fi environments.

Idaho National Laboratory’s LENS developed a pattern matching-based location tracking (Kurt & Milos, 2008), With the help of topological counter propagation network (CPN) with K-nearest neighbor vector mapping, LENS not only guarantees the high location tracking accuracy, but also alleviates the computation cost. Similar work on pattern matching-based location tracking in Wi-Fi environments can be found in Outemzabet and Nerguizian (2008), Ahmad et al. (2006), Fang and Lin (2008), Badawy and Hansen (2017), Zhou, Xu, and Ma (2010), Zhou, Xu, and Tang (2010). In Outemzabet and Nerguizian (2008), Outemzabet and Nerguizian investigated the way to the accuracy enhancement of artificial neural network (ANN) based location tracking by particle filtering and digital compass. Particle filtering is used to modify the parameters of the people’s non-linear tracking models, while the digital compass can help to estimate the motion orientations. In Ahmad et al. (2006), a modular multi-layer perceptron (MMLP) is
considered to improve the location certainty and the incomplete signal processing capability. MMLP consists of five key modules including the RSS recording and smoothing, data normalization, perceptron training, data post processing, and position estimation. Fang studied the discriminant-adaptive neural network (DANN) based location tracking (Fang & Lin, 2008). Compared to MMLP, DANN compresses the raw RSS data into a low dimensional space, and then extracts the most beneficial discriminative components to train a reliable location tracking system. A comprehensive comparison between pattern matching and decision tree (DT) for the location tracking are discussed in Badawy and Hasan (2007). In Badawy and Hasan (2007), the DT performs better than the pattern matching in location accuracy because the inappropriate number and structures of neurons could seriously deteriorate the accuracy of pattern matching based location tracking systems.

2.2. Propagation model-based location tracking

The propagation model in Emery and Denko (2007), Alasti et al. (2009) shows that the mean of received RSSs decreases logarithmically with the propagation distance in open environment. However, in the indoor environment, if the path loss exponents are assigned inappropriately or the small-scale fading dominates over the large-scale fading, the propagation model based location tracking system cannot be effective. In Ahn and Yu (2008), Ahn and Yu investigated the combination of Wi-Fi, UWB, and ZigBee technologies to achieve the location tracking. In their system (Ahn & Yu, 2008), a finer radio propagation model was built up based on the iterative calibration of the parameters for propagation models. Narzullaev and coauthors in Narzullaev et al. (2008) compared the reliability of one-slope, modified one-slope, and multi-wall propagation models. The one-slope model is built upon the assumption of log-distance path loss property. Compared to the one-slope model, the modified one-slope model has the main advantages of finer granularity of prediction points, as well as the reduced sample collection time. Different from the one-slope and modified one-slope models, the multi-wall model took into account the path loss caused by the walls and floors. More studies on propagation model based location tracking systems in Wi-Fi environments can be found in Widyawan et al. (2007), Liu et al. (2012), Shen et al. (2011), Wang et al. (2005).

The above work offered a variety of technologies to facilitate the location tracking by using the existing widespread Wi-Fi networks. However, there are still two significant but open problems in this area. One is about the dimension flood of RSS fingerprints caused by the significantly increasing number of APs. To solve this problem, Fang and coauthors in Feng et al. (2010), Au et al. (2012) developed a compressive sensing approach to recover the whole sparse signals from a small number of RSS measurements. Another drawback is about the laborious cost for the fingerprint calibration. To avoid this laborious cost, we have introduced a novel adaptive mobility map in Zhou et al. (2013), which can be used to track people’s locations by shotgun read matching.

The SCaNME system proposed in this paper is distinct from the above location tracking systems in three aspects. First, the SCaNME relies on the spectral clustering to examine the similarities of RSS samples in both the RSS and timestamps. After the spectral clustering, the RSS dimension flood can be avoided by using Laplacian embedding-based dimensionality reduction. The Laplacian embedding is featured with RSS locality-preserving property and RSS clustering. Second, the SCaNME is built upon the unlabeled samples which have no explicit information about their physical coordinates, so that the time and laboring cost for location fingerprinting is not considered, and thereby the location tracking process becomes flexible and reliable. Finally, the SCaNME takes advantage of Allen’s logics to record the people’s activities in target environment, thus it is capable of providing more accurate tracking than the conventional location tracking systems.

2.3. Purpose of mobility map construction

As discussed in Zhou et al. (2013), we introduced a way to construct an unlabeled mobility map in which the similar RSS samples recorded within a small time interval and with small RSS difference can be clustered together to form a location point (LP). To construct the mobility map, we first use Kullback–Leibler (KL) divergence to examine the similarity of each pair of LPs, and then assemble these LPs into a graph by using the time stamped transition relations among the LPs.

In our experiments, each person is equipped with a Samsung GT19100 Android phone to record the Wi-Fi RSS measurements following his or her activities in HKUST campus. Each measurement consists of the time stamped RSS values and the associated MAC addresses of hearable APs. In the off-line phase, the sporadically recorded measurements are used to construct an unlabeled mobility map \( G = (V_C, E_p) \) in which the vertices \( C \in V_C \) and edges \( \varphi \in E_p \) represent the clusters of similar measurements and the transition relations among the clusters, as discussed in Wang et al. (2012). Based on the mobility map, the LPs involved in people’s activities can be identified by using Allen’s logics. Then, in the on-line phase, the location tracking is composed of four key steps: (1) collection of new data; (2) selection of candidates; (3) location tracking by the maximum likelihood estimation (MLE) criterion; and (4) path reconstruction.

3. Architecture of SCaNME location tracking

There are two phases involved in SCaNME system, the off-line mobility map construction phase and the on-line path reconstruction phase. An overview of our proposed SCaNME system is illustrated in Fig. 1. After the mobility map is constructed, we track the people’s positions by matching the newly collected RSS data into the pre-stored RSS samples. Details of each step in SCaNME system are described below.

3.1. Review of mobility map construction

Mobility map construction consists of: (1) shotgun read collection; (2) spectral clustering on shotgun reads; (3) shotgun reads matching by KL divergence; (4) Transition probabilities calculation.

Wi-Fi networks

Cell phones

Off-line phase

1) Shotgun read collection
2) Spectral clustering on shotgun reads
3) Shotgun reads matching by KL divergence
4) Transition probabilities calculation

On-line phase

5) Person’s motion activities
6) Mobility map
7) Collection of new data
8) Selection of candidates
9) Location tracking
10) Path reconstruction

Cluster matching

Feedback

MLE

Initialization

Splicing

Fig. 1. Block diagram of SCaNME system.
matching by KL divergence; and (4) transition probability calculation.

We first represent a shotgun read by ordering the person’s recorded continuous time RSS measurements in chronological order. The long shotgun read is fragmented into short ones to decrease the computation time for each read, as discussed at the end of Section 3. If there are N raw shotgun reads, we can represent the ith read by \( R^{i} = \{ \mu_{i1}, \ldots, \mu_{i2} \} \) where \( \mu_{ij} \) and \( N \) stand for the ith recorded RSS measurement and the number of measurements in read \( i \), respectively. By the assumption of time interval \( \delta \), the absolute timestamp of the kth measurement \( \mu_{ik} \) in read \( i \) is calculated by \( T_{ik} = T_{i} + (k-1)\delta \) where \( T_{i} \) is the absolute timestamp of the first measurement \( \mu_{i1} \) in read \( i \); and \( (k-1)\delta \) is the relative timestamp of the \( k \)th measurement \( \mu_{ik} \) with respect to \( \mu_{i1} \). Moreover, each measurement can be represented by an M-dimensional vector where \( M \) is the number of hearable Wi-Fi APs in target domain.

Then, spectral clustering on shotgun reads is realized by the following three steps: (1) calculation of similarity matrix on each read; (2) Laplacian embedding into a low-dimensional space from the raw measurement space; and (3) K-means clustering in low-dimensional space to classify the measurements into different clusters.

In each shotgun read (e.g., \( R^{i} \)), the similarity matrix is denoted by \( S^{i} = [S_{ij}^{i}]_{1 \leq i, j \leq N} \) where \( S_{ij} = \exp(-\alpha \rho F_{ij}^{i} - \beta \tau Fr(T_{i}, T_{j})) \) stands for the similarity of \( \mu_{ij} \) and \( \mu_{jk} \). \( \alpha \) and \( \beta \) are the weighting coefficients for the RSSs and timestamps. The feature of RSS \( F_{ij}^{i} \) and the features of timestamp \( Fr(T_{i}, T_{j}) \) are calculated by

\[
F_{ij}^{i} = \| \mu_{ij} - \mu_{jk} \|_{2} = \max_{1 \leq k \leq N} \| \mu_{ij} - \mu_{ik} \|_{2}, \quad Fr(T_{i}, T_{j}) = |T_{ik} - T_{jk}|/(N' - 1)\delta
\]

To preserve the similarities of RSS measurements after the Laplacian embedding from the raw measurement space (of dimension \( M \)) into a low-dimensional space (of dimension \( k'(K' < M) \)), we need to ensure that any two measurements (e.g., \( \mu_{ij} \) and \( \mu_{jk} \)) have large similarity have the mapping points (e.g., \( r_{i}^{j} \) and \( r_{j}^{j} \)) in the neighborhood as well. Then, we can define our objective function as

\[
F(r^{j}) = \sum_{l=1}^{k} (r_{i}^{j} - r_{l}^{j})^{2} S_{lj}' \quad \text{where} \quad r^{j} = (r_{1}^{j}, \ldots, r_{K'}^{j})^{T}
\]

should be minimized, such that

\[
\vec{r}^{j} = \arg\min_{r^{j}} \{ F(r^{j}) \} = \arg\min_{r^{j}} \{ (r^{j} - \vec{r}^{j})^{T} L^{j} (r^{j} - \vec{r}^{j}) \}
\]

where \( L^{j} = D^{j} - S' \) is the Laplacian matrix. \( D^{j} \) is a diagonal matrix with \( D_{lj}' = \sum_{j=1}^{K'} S_{lj}' \). By using the Lagrange multiplier method, we can convert the problem in Eq. (2) into

\[
\vec{r}^{j} = \arg\min_{r^{j}} \{ \lambda \}
\]

where \( \lambda \) is the generalized eigenvalue of \( L^{j} \). As discussed in Zhou et al. (2013), the eigenvectors \( \{ r_{1}^{j}, \ldots, r_{K'}^{j} \} \) corresponding to the \( k' \) smallest eigenvalues \( \{ \lambda_{1}' \leq \cdots \leq \lambda_{K'}' \} \) should be selected as the basis of the low-dimensional space to minimize \( Q(\vec{r}^{j}) \), as shown in Eq. (4).

\[
\min_{Q(\vec{r}^{j})} = \text{min}(\{ \text{tr}(\Psi' \Psi) \}) = \text{min}(\{ \text{tr}(\Psi' \Psi) \})
\]

where \( \Psi' = (\vec{r}_{1}, \ldots, \vec{r}_{K'})^{T} \) and \( \vec{r}_{ij}' = (\vec{r}_{i1}', \ldots, \vec{r}_{iK'}')^{T} \). Therefore, we can map the raw shotgun read \( R^{i} \) into \( R = \{ \vec{r}_{1}, \ldots, \vec{r}_{K'} \} \).

After running the K-means clustering on \( R' \), we can obtain the new clustered read \( \vec{r}^{j} = \{ C_{j}^{1}, \ldots, C_{j}^{F} \} \) where \( C_{j}^{1} \) and \( \Phi^{j} \) stand for the rth cluster and the number of clusters in \( \Phi^{j} \). The value range of \( \Phi^{j} \) is from \( N'_{j} + 1 \) to \( \lceil N' \delta/T_{ij}' \rceil + 1 \) where \( N'_{j} \) is the number of forks of the real path on which the read \( \epsilon \) is recorded; \( T_{ij}' \) is the average timestamp difference between the neighborhood clusters; and \( \lceil N' \delta/T_{ij}' \rceil \) stands for the largest integer which is smaller than \( N' \delta/T_{ij}' \).

We calculate the KL divergence \( x_{ij} \) of RSS distributions of one cluster \( C_{j}^{r} \) with another one \( C_{j}^{r'} \) in Eq. (5).

\[
x_{ij} = \sum_{l=1}^{M} \sum_{\eta=0}^{\infty} \left( P_{r}(\eta) \log_{2} \left( \frac{P_{r}(\eta)/P_{r'}(\eta)}{M_{\eta}} \right) \right) / M
\]

where \( P_{r}(\eta) \) and \( P_{r'}(\eta) \) stands for the RSS distribution of the rth cluster \( C_{j}^{r} \) on read \( r \) and from the rth AP. For instance, the probability of RSS value \( \eta \) under the distribution \( P_{r'} \) is denoted as \( P_{r'}(\eta) \). \( M_{\eta} \) denotes the maximum RSS value.

Finally, we obtain the transition probabilities between the neighborhood LPs in Eq. (6). The transition probability matrix is defined as \( \Phi = \frac{\varphi_{\epsilon-\mu}}{\varphi_{\epsilon-\mu}} \) where \( N'_{j} \) is the number of LPs.

\[
\varphi_{\epsilon-\mu} = \frac{\text{Number of transitions from } L_{0_{\epsilon}} \text{to LP}}{\text{Number of transitions from } L_{0}}
\]

where a transition occurs if there is a measurement in \( L_{0} \) leading to a consecutive one in \( L_{0} \) without visiting any other clusters. As discussed in Wang et al. (2012), we name the LPs where the people stay for a long time as the personal common locations (PCLs) (e.g., the labs, restaurants, and dormitories).

3.2. Steps of location tracking in SCaNME system

After the mobility map is constructed, there are three steps involved in the on-line location tracking phase: (1) location initialization by using the initially collected RSS measurements; (2) selection of candidate LPs where the person is most probably located; (3) iterative location tracking by the MLE criterion; and (4) path reconstruction based on the time stamped chronological tracking LPs. These steps are described below.

Step 1: As shown in Fig. 2, we denote the number of paths which start from the LP \( L_{0} \) as \( N_{0_{\epsilon}} \) and the 6th LP on path k as \( L_{0_{\epsilon}}^{k-1} \) where \( L_{0_{\epsilon}}^{k-1} = \cdots = L_{0_{\epsilon}}^{1} = L_{0_{\epsilon}} = L_{0}, v = 1, \ldots, N_{0_{\epsilon}}, k = 1, \ldots, N_{0_{\epsilon}} \) By using the MLE method, we can obtain the probability of each LP to be selected as the people’s tracking LP, as illustrated in Eq. (7).

\[
p_{0}^{(v)} = \frac{\sum_{u=1}^{N_{0_{\epsilon}}} \varphi_{\epsilon-\mu}^{(v)} p(L_{0_{\epsilon}}^{u}) p(L_{0_{\epsilon}}^{u}) | \eta_{\text{new}} \rangle}{\sum_{u=1}^{N_{0_{\epsilon}}} \sum_{v=1}^{N_{0_{\epsilon}}} \varphi_{\epsilon-\mu}^{(v)} p(L_{0_{\epsilon}}^{u}) p(L_{0_{\epsilon}}^{u}) | \eta_{\text{new}} \rangle}, u = 1, \ldots, N_{0_{\epsilon}}
\]

where \( p(L_{0_{\epsilon}}^{u}) | \eta_{\text{new}} \rangle \) is the time interval of the mean of relative timestamps of the measurements in \( L_{0_{\epsilon}}^{u} \) and the relative timestamp of locating the next tracking LP \( L_{0_{\epsilon}}^{u} \) is the LP which has the largest number of
measurements with the relative timestamps not larger than $T_{lu} + T_u$ on path $k$. For a new measurement set $\eta_{new}$, $p(L_k^0(T_u)|\eta_{new})$ is the probability with respect to the relative timestamps in the range of $[T_{lu} + T_u - 3\sigma, T_{lu} + T_u + 3\sigma]$ under the distribution of the relative timestamps of measurements in $L_k^0(T_u)$. Therefore, we should choose $L(0)$ as the people’s tracking LP, such that

$$L(0) = \arg \max_{x_u} \left\{ p(0|x_u) \right\}$$

$$= \arg \max_{x_u} \left\{ \sum_{k=1}^{N_0} \phi_k L_k^0(T_u) p(\eta_{new}|L_k^0(T_u)) \right\}$$  \hspace{1cm} (8)$$

where $p(\eta_{new}|L_k^0(T_u))$ is the prior probability of the mean of the relative timestamps of measurements in $\eta_{new}$ under the distribution of the relative timestamps of measurements in $L_k^0(T_u)$. For simplicity, we assumed that $p(\eta_{new}|L_k^0(T_u))$ is inversely proportional to the KL divergence between $L_k^0(T_u)$ and $\eta_{new}$. Then, Eq. (8) becomes

$$L(0) = \arg \max_{x_u} \left\{ X_u \right\}$$

$$= \arg \max_{x_u} \left\{ \sum_{k=1}^{N_0} \phi_k L_k^0(T_u) X_u \right\}$$  \hspace{1cm} (9)$$

Step 2: Go back to step 2 to locate the next tracking LP until the people ceases moving. Here, the jth tracking LP is denoted as $L(j)$. Moreover, based on the people’s activity learning from the previously constructed path “Path$_{L_0^0 \ldots L_{j-1}^0} = (L(0), \ldots, L(j))$”, we can narrow down the searching space for the $(j+1)$th tracking LP. The detailed discussion on activity learning by Allen’s logics is provided in Section 4.

3.3. Read length constraint

Since the raw shotgun reads may be too long, intensive computation problem may arise. Then, we have to segment any long shotgun reads into small ones. Table 1 shows the computation time needed for spectral clustering in different length conditions by using MATLAB 7.10.0 (R2010a) under WINDOWS XP system. All the computations are run on a PC with Intel Core i3-2120 CPU. For the sake of simplicity, we segment the raw read into small ones in different lengths with the same cluster number $\Psi = 10$.

In Table 1, we observe that the time cost for spectral clustering increases with the length of read. When the length of read exceeds 600 measurements, the averaged time cost increases by more than 100 s for each additional 100 measurements. Hence, to guarantee the time efficiency, we restrict the lengths within 600 which allow 2 min processing for the spectral clustering in off-line phase.

<table>
<thead>
<tr>
<th>Length of reads (or number of measurements)</th>
<th>Time cost ($)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Test 1</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>--------</td>
</tr>
<tr>
<td>100</td>
<td>0.36</td>
</tr>
<tr>
<td>200</td>
<td>2.25</td>
</tr>
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<td>223.80</td>
</tr>
<tr>
<td>800</td>
<td>399.02</td>
</tr>
</tbody>
</table>

4. Activity learning by Allen’s logics

In addition to the steps of location tracking in SCaNME system, the SCaNME also instantaneously learns the person’s activities from the previously reconstructed paths, in order to accurately and effectively locate the tracking LPs on the paths. To meet this goal, we use Allen’s logics as a new metric to investigate the person’s motion activities conveyed from the mobility map. Therefore, the probability of a LP being the tracking LP should also depend on the person’s prior knowledge of locations on a daily, weekly or monthly basis.

4.1. Temporal relations of activities

First of all, as depicted in Fig. 3, we can represent the person’s each activity (e.g., Sleep, Work in lab, Have lunch, Alone, etc.) as a function of time. Moreover, we define three types of activity status: (1) natural status (i.e., Morning, Afternoon and Evening); (2) individual status (i.e., Stationary and Moving); and (3) circumstantial status (i.e., Alone and Surrounded). In Fig. 3, “BP” is denoted as the cut-off time point of two consecutive activities. Therefore, the temporal relations of every two activities can be represented by Allen’s logics. As discussed in Allen [1983], there are 13 Allen’s logics to be used: equals (=), before (<), after (>), during (d), contains (c), overlaps (o), overlapped-by (oi), meets (m), met-by (mi), starts (s), started-by (si), finishes (f), and finished-by (fi), as shown in Fig. 4. For instance, we have the temporal relations of the activities: Morning (o) Work in lab (s) Stationary (mi) Moving (f) Surrounded (mi) Alone.

4.2. Construction of temporal logic graph

Based on the temporal relations of activities, we can construct a temporal logic graph $G_s = (V_A, E_A)$ in which the vertices $v_A \in V_A$ and edges $e_A \in E_A$ stand for the person’s activities and the related Allen’s logics, as shown in Fig. 5.

By using temporal logic graph, if the person is detected to be stationary (Stationary$^1$ or Stationary$^2$) in the afternoon, there are two possible activities: “Work in lab” and “Have lunch in the restaurant”. In this case, we can only consider the LPs close to the lab or restaurant as the candidate LPs.

Moreover, some activities are probably missing or indistinguishable in temporal logic graph. For instance, there are three missing activities (i.e., BP1: walk from dormitory to school gate; BP7 and BP10: walk from restaurant to lab) and two indistinguishable activities (i.e., the activities before and after BP3: walk though lobby) in Fig. 3. For the missing activities, we can find that the KL divergence between the newly recorded RSS distribution and the distributions in the existing LPs is significantly large. In this case, we record this activity into the temporal logic graph as new activity. For the indistinguishable activities, the person’s activities are very likely to be in the moving status. Thus, the
indistinguishable activities can only last for a very short duration. However, the detailed discussion on this work is out of the scope of this paper.

Finally, the purpose of activity learning by Allen’s logics is to predict the person’s possible activities and select the most likely candidate LPs for the location tracking from the previously
constructed paths in the on-line phase. Different from the conventional location tracking systems, the probabilities of candidate LPs in the SCaNME system depend on not only the KL divergence between the newly recorded RSS distributions and the distributions in the LPs, but also the predicted possible activities from Allen’s temporal logic graph.

5. Experimental results

5.1. Data collection

The efficiency and effectiveness of the location tracking by the SCaNME system is verified in one part of the HKUST campus.

Fig. 7. Similarity matrices of shotgun reads.

Fig. 8. Eigenvectors for low-dimensional space reconstruction.
The volunteers carrying the Samsung GT19100 Android phones collected 2017 Wi-Fi RSS measurements (of dimension 588) following their routine activities on Monday. They used the same wireless card vendor during both the off-line and on-line phases to reduce the ambiguity of displayed RSS values (Kaemarungsi, 2006; Mengual, Marban, & Eibe, 2010).

In Mengual et al. (2010), the authors tested four different wireless cards, in terms of the range and measurement of RSS, and found that there could be a difference of more than 20 dB between the 3Com and Ovislink cards. Moreover, the US Robotics card implemented the RSS as a percentage, but not in dBm which is used...
by the 3Com, Ovislink, and Zoom cards. Because the displayed RSS values at the terminal significantly rely on the types of wireless cards, most of the existing Wi-Fi RSS-based location tracking systems required that the cards used in off-line RSS training and on-line RSS testing should be the same module. However, the validation of SCaNME in the context of using different wireless cards forms an interesting work in future.

We segment the raw long-length shotgun reads into four small reads with lengths of 500, 501, 613, and 403, respectively, as shown in Fig. 6. The 4 reads are recorded on four paths: (1) path one: from “School gate” to “Lab” (Northern (Main) Entrance → Entrance Piazza → Academic Building); (2) path two: from “Lab” to “Restaurant” (Academic Building → Atrium → Library); (3) path three: from “Restaurant” to “Dormitory” (Library → Bridge Link → Visitor Center → University Center & Apartments); and (4) path 4: from “Dormitory” to “Lab” (University Center & Apartments → Atrium → Academic Building).

5.2. Mobility map construction

(1) Similarity matrices:
The first step of mobility map construction is to calculate the similarity matrices of the recorded shotgun reads. For the sake of simplicity, we distribute the equal weighting coefficient for the RSSs and timestamps, which means \( \alpha_R = \alpha_T = 0.5 \). Therefore, we can obtain the four similarity matrices in Fig. 7.

(2) Low-dimensional space reconstruction:
Due to the high dimensionality of the raw shotgun reads, we reconstruct the raw measurements in a low-dimensional space which is expanded by a subset of eigenvectors corresponding to the smallest eigenvalues. In our experiments, we set the eigenvalues for the selected eigenvectors smaller than 0.96. Therefore, because there are only three eigenvectors to be selected as the basis of the reconstructed low-dimensional space, each raw measurement is reconstructed as a three-dimensional vector, as shown in Fig. 8. For instance, the 200th measurement in read 1 (i.e., \( l_{1200} \)) is reconstructed as \( \tilde{l}_{1200} = \begin{pmatrix} 0.0025 \\ 0.0015 \\ 0.0027 \end{pmatrix} \).

(3) Spectral clustering:
As discussed before, after the spectral clustering, the measurements with higher similarities in both the RSSs and timestamps are more likely to be clustered into the same LP. By setting \( \delta = 1 \) s and \( T_p = 50 \) s, we can obtain \( \Phi^1 = 11 \), \( \Phi^2 = 11 \), \( \Phi^3 = 13 \), and \( \Phi^4 = 9 \). Then, the results of spectral clustering on each read are shown in Fig. 9.
Topological structure

The final step of mobility map construction is to merge the LPs which have the KL divergence smaller than the matching threshold. In Fig. 10, we only focus on the KL divergence of the LP pairs from read 2 to reads 1 and 4, and the LP pairs from read 3 to reads 2 and 4 because the hearable APs for the other LP pairs are much different. To be clearer, we set the KL divergence of the LP pairs which have 294 different hearable APs as 2. Based on the results of KL divergence in Fig. 10, we merge the LPs which have the KL divergence smaller than 0.6, connect the adjacent LPs which have the non-zero transition probabilities (see Eq. (6)), and consequently obtain the mobility map in Fig. 11.

In Fig. 11, we can obtain 6 PCLs where the person has stayed for a long time in mobility map. The notations “GL”, “LR”, “RD”, and “DL” stand for the LPs in reads 1, 2, 3, and 4, respectively. By using the temporal logic graph, we can identify the “Lab” (PCL1 and PCL2), “Restaurant” (PCL3 and PCL4), “Dormitory” (PCL5), and “School gate” (PCL6). For instance, there is only one chain of logic relations “Stationary” m Moving m Stationary (in Fig. 5) being in accordance with the person’s activities with both the starting and ending clusters in read 1 belonging to the PCLs. Moreover, by using the Allen’s logic graph, there are two possible paths: (1) path from dormitory to lab; and (2) path from school gate to lab. Because the KL divergence between the starting clusters in read 1 and the LPs close to the dormitory is significantly large, we can make a reasonable conjecture that the person’s motion path is very likely from school gate to lab. Therefore, PCL6 and PCL1 should represent the “School gate” and “lab”, respectively.

5.3. Performance of location tracking

5.3.1. Experimental setup

In the following results, we examine the tracking precision and reliability of the SCaNME system in comparisons with other four representative location tracking systems, RADAR, Horus, Nibble, and ANN. The tracking precision and reliability are defined as the probability of locating the person’s positions on the correct path and the consistency between the directions of the real paths and reconstructed paths, respectively. As shown in Fig. 12, we select two activities as our testing cases: (1) stationary case: the person is stationary at “School gate” (i.e., the person’s real location is in PCL6) in the morning; and (2) moving case: the person walks from “Restaurant” to “Lab” through “Dormitory” (i.e., the person’s real path is from PCL3 or PCL4 to PCL2 through PCL5) in the evening. The recorded reads for the testing are shown in Fig. 13.
5.3.2. Location tracking

5.3.2.1. Case 1: stationary case. If the person is stationary in the morning, he or she is probably in the two activity status: “Stationary” or “Stationary” based on the temporal logic graph in Fig. 5. In this case, the candidate LPs considered for location initialization can only be located on paths one and four. As can be seen in Fig. 14, because GL9 which belongs to PCL6 always has the smallest KL divergence with the increase of time interval, the transition probabilities from GL9 to the other LPs should equal to zero, which means the tracking precision by SCANME system equals to 100%. Therefore, the probability of each candidate LP to be selected as the person's tracking LP is inversely proportional to the KL divergence between the newly recorded RSS distributions and the distribution in each candidate LP, as shown in Fig. 14. Moreover, the tracking results by RADAR, Horus, Nibble, and ANN location tracking systems are presented in Fig. 15. For the sake of simplicity, we set the same time interval for every two consecutive LP tracking as Tu = 50 s.

In Fig. 15, the nearest neighbor(s) in signal space (NNSS) (k = 1 and 3) in RADAR are used for the evaluations. k = 1 which is also called the nearest neighbor (NN) is recognized as a baseline algorithm designed for RADAR location tracking, while k = 3 has been proved in Bahl and Padmanabhan (2000) that the best accuracy can be achieved. Although both the Horus and Nibble are based on the Bayesian theory, the most significant difference is that the former one uses the Gaussian curves to fit RSS distributions, while the latter one relies on the histograms of RSS values. A three-layer back propagation structure is used for the training of ANN model. Because there is no physically labeled samples involved in off-line phase, we select the LPs in mobility map as the alternative fingerprints for RADAR, Horus, Nibble, and ANN location tracking systems. The results of tracking LPs by SCANME, RADAR, Horus, Nibble, and ANN location tracking systems are shown in Fig. 16.

As shown in Fig. 16, by using the temporal logic graph in Fig. 5, we can find that the person’s activity “Wait at school gate” can be revealed by SCANME, RADAR, Horus and ANN because their results of tracking LPs belonging to PCL6 (or School gate) are invariant with the increase of timestamps. To be clearer to illustrate these results, we define the tracking reliability for the stationary case (Rstationary) as

\[ R_{\text{stationary}} = 1 - \frac{\text{Number of measurement transitions}}{\text{Measurement length}} \]  

(10)

where a measurement transition is counted if there is a tracking LP leading to another consecutive tracking LP. In the condition of sample rate 1 Hz, the measurement length equals to the time duration (in second). The results of tracking reliability by SCANME, RADAR, Horus, Nibble and ANN location tracking systems are compared in Fig. 17.

From Fig. 17, we can find that: 1) SCANME performs best because there is no measurement transition involved; 2) by RADAR, k = 3 performs better than k = 1 in tracking reliability as expected; 3) the tracking reliability of Horus is significantly higher compared to Nibble due to the small number of measurements in each LP; and 4) ANN performs well in our experiments, while if the ANN has not been sufficiently trained or the overmatching occurs, the reliability of ANN could be significantly deteriorated.

5.3.2.2. Case 2: moving case. If the person is detected to be in move in the evening, there are only two possible activities: “Leave for dinner” and “Walk from lab to dormitory” based on the Allen’s logics “Leave for dinner (=) Moving” \(^{2}\) and “Walk from lab to dormitory (=) Moving” \(^{4}\). In this case, only the LPs on paths two and three could be selected as the candidate LPs for the location initialization. By using the Eq. (9), we can calculate the value \(Z^{j}_{u} \) of each candidate LP, as shown in Table 2.

Based on Fig. 11 and Table 2, the PCL4 (Restaurant: LR4, LR3 and RD13) is selected as the person’s initial location because the

![Fig. 16. Results of tracking LPs in stationary case.](image)

![Fig. 17. Results of tracking LPs in stationary case.](image)

![Fig. 18. Value \(Z^{j}_{u} \) on path three.](image)

![Table 2](image)
maximal value $Z_u(2.885)$ is achieved in PCL4. Thus, the consecutive tracking LPs can only be located on path three until the reconstructed path reaches PCL5. To be clearer, Fig. 18 illustrates the three largest $Z_u(l = 0, \ldots, 10)$ with respect to each LP tracking on path three. In SCaNME, we select the LPs with the largest $Z_u(l)$ as the tracking LPs. For the comparison, the reconstructed paths by SCaNME, RADAR, Horus, Nibble and ANN location tracking systems are shown in Fig. 19.

When the person arrives at PCL5 (Dormitory), we cannot make a reasonable conjecture on which direction the person walks forward in because there is no relative activity recorded in Allen’s temporal logic graph. As can be seen in Fig. 5, if the person arrives at PCL5 in the evening, the person should be stationary in Dormitory (Watch TV or Sleep). Therefore, we first need to determine the direction in which the person walks forward (i.e., walk forward to the Lab or walk back to the Restaurant). Thus, both the LPs on paths three and four should be selected as the candidate LPs with the timestamps from 600s to 800s. Similarly, the three largest $Z_u(l = 11, \ldots, 15)$ and the corresponding results of path tracking are shown in Figs. 20 and 21, respectively.
From Figs. 19 and 21, the constructed path by SCaNME is closest to the real path compared to the other location tracking systems. Moreover, the direction of reconstructed path should also be significantly concerned. For instance, although the reconstructed path from RD11 to RD10 by the 11th LP tracking in Horus (see Fig. 19(d)) is overlapped with the real path, the real path and the path reconstructed by Horus are in different directions (or named as the paths in reversed directions). To illustrate this point clearer, we define the tracking reliability for the moving case ($R_{\text{moving}}$) as

$$R_{\text{moving}} = 1 - \frac{\text{Number of reversed transitions}}{\text{Sample length}}$$

From Figs. 19 and 21, the constructed path by SCaNME is closest to the real path compared to the other location tracking systems. Moreover, the direction of reconstructed path should also be significantly concerned. For instance, although the reconstructed path from RD11 to RD10 by the 11th LP tracking in Horus (see Fig. 19(d)) is overlapped with the real path, the real path and the path reconstructed by Horus are in different directions (or named as the paths in reversed directions). To illustrate this point clearer, we define the tracking reliability for the moving case ($R_{\text{moving}}$) as

$$R_{\text{moving}} = 1 - \frac{\text{Number of reversed transitions}}{\text{Sample length}}$$

Fig. 20. Value $Z_u^{(l)}$ on path four.

Fig. 21. Results of path tracking on path four.
where a reversed transition is counted if there is a tracking LP leading to another consecutive tracking LP on the path in reversed direction. The tracking reliability for the SCaNME, RADAR, Horus, Nibble, and ANN location tracking systems is shown in Fig. 22.

From the tracking reliability in Figs. 17 and 22, we can conclude that: (1) for both the stationary and moving cases, SCaNME has guaranteed 100% tracking reliability; (2) RADAR with \( k = 3 \) performs better than the \( k = 1 \) condition; (3) by using the Bayesian theory, Horus outperforms Nibble in tracking reliability; and (4) the tracking reliability of ANN cannot be effectively guaranteed due to the difficulty of neural network training.

### 6. Conclusion

Location tracking in large-scale environments is addressed as a passport to the all-weather and seamless LBSS in future. How to use widely-deployed Wi-Fi networks to perform the highly accurate and cost efficient location tracking remains to be an open issue. The conventional Wi-Fi RSS-based location fingerprinting involves a plethora of time and laboring cost for fingerprint recording. However, in SCaNME, we first use the sporadically recorded Wi-Fi RSS measurements to create a mobility map in which the neighborhood LPs are connected by non-zero transition probabilities. Second, by examining the temporal logic relations of activities observed from the mobility map, we can construct a temporal logic graph to provide some guidance to the selection of candidate LPs for location tracking. Finally, by following MLE criterion, the SCaNME iteratively locates the person’s tracking LPs which have the smallest KL divergence and also reconstruct the motion paths by connecting the consecutive tracking LPs.

Both the theoretical analysis and experimental results provide insights about the efficiency and effectiveness of the proposed SCaNME location tracking system. The unlabeled mobility map and the corresponding location tracking algorithm developed in this paper are adaptive and reliable; thus are applicable to the Wi-Fi environments for location tracking to satisfy the future requirements of LBSS. Our work opens up a new direction to explore efficient and accurate location tracking systems in large-scale Wi-Fi environments. Since the SCaNME is built upon the unlabeled fingerprints which have no explicit information of their physical coordinates, the first contribution of this paper is about the cost saving for location tracking compared to the conventional RSS fingerprinting-based Wi-Fi location tracking systems. The second contribution is about the description of anonymous environment. In concrete terms, the mobility map constructed by SCaNME can be used to roughly describe the layout of anonymous environments. The third contribution is to record the people’s activities by using the temporal logic graph in SCaNME system. More specifically, in the environments where the people’s movement patterns have been recorded, it is worth to apply SCaNME to other existing RSS-based location tracking systems to obtain a refined location estimate for the sake of providing better user-centric location information.

For longer term, one is more likely to integrate the sporadically recorded Wi-Fi RSS measurements and the timestamps to label the LPs in large-scale environments without any cumbersome work for fingerprint calibration. However, there are three directions to be concerned in future. First, the validation of SCaNME in the context of using different wireless cards. Second, the system adaptation and reliability of SCaNME for the people having different movement patterns from different organizations. Third, the current SCaNME system continuously scans the Wi-Fi RSS samples, and this involves of a high energy consumption. Therefore, the devise of an energy-efficient scan policy also forms an interesting topic for our future investigation.

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