This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

MapSense: Mitigating Inconsistent WiFi Signals using Signal Patterns and Pathway Map for Indoor Positioning

Xuan Du, *Student Member, IEEE,* Kun Yang, *Senior Member, IEEE* and Dongdai Zhou

***Abstract*—The indoor positioning technology plays a significant role in the scenarios of the Internet of Things (IoT) which require indoor location context. In this paper, the WiFi signals under modern enterprise WiFi infrastructure, signal patterns between coexisting access points (APs) and signals' correlation with indoor pathway map are investigated to address the problem of inconsistent WiFi signal observations. The sibling signal patterns (SSP) are defined for the first time and processed to generate Beacon APs which have higher confidence in positioning. The spatial signal patterns are used to bring the estimated location into a limited area through signal coverage constraint (SCC). A positioning scheme using SSP and SCC is proposed and shows improved positioning accuracy. The proposed scheme is fully designed, implemented and evaluated in a real-world environment, revealing its effectiveness and efficiency.**

***Index Terms*—indoor positioning, WiFi fingerprint, indoor map, signal pattern, enterprise WiFi, context sensing.**

I. INTRODUCTION

With the surge of IoT systems and its broad applications in real life, the indoor location is valuable information to achieve various context-aware services, and hence the demand of indoor positioning solutions are on the increase dramatically. The application scenarios of indoor positioning in IoT include Smart Home, e.g. location-based automated heating or lighting control, and E-Health Care, e.g. tracking and monitoring the movement of patients. Indoor positioning is a well-known problem and attracts a lot of research efforts in the last decade. Researchers from both academia and industry are attempting to seek the signals of opportunity for indoor positioning. The work in this paper is extended based on work in [1].

In recent years various positioning technologies for indoor use have emerged. Meanwhile, many hybrid solutions using multiple technologies are proposed. The inertial sensors are commonly fused with other technologies to provide prediction or correction. Among existing technologies, the use of WiFi is a popular approach to bring indoor positioning into practice, because WiFi APs are already deployed extensively in most public places like hospital and shopping mall and most off-the-shelf mobile devices are already equipped with WiFi communication modules [2]. In the WiFi-based positioning, the APs act as the ready-to-use beacons for positioning and the off-the-shelf mobile devices are the targeted positioning object. The wide deployment of WiFi infrastructure and the ubiquity of WiFi-integrated mobile devices have provided an enormous opportunity for indoor location-based services [3].

Fingerprinting is a widely-used technique for positioning using WiFi. Fingerprinting technique is a process of collecting signal and associating signal features with physical locations on the premise that AP locations are not known. Based on the association, various algorithms are applied to find the best-matched signal features, i.e., the location of a user. The WiFi fingerprint is defined as a mapping of APs' received signal strength (RSS) observations to locations. The RSS observation is a vector of RSS from different APs that are reachable at the location. Fingerprint-based positioning usually consists of two stages: offline site survey and online positioning. The site survey is conducted by a WiFi-compatible mobile handheld (MH) to collect WiFi fingerprint at every reference point (RP) in the interesting area. The fingerprints collected at all the reference points constitute a fingerprint database to serve online positioning. In positioning phase, the real-time RSS observed by a WiFi-compatible MH is compared with RSS observations in fingerprint database to find the best-matched one. The corresponding location of the best-matched RSS observation is returned as user's location [4].

In this paper, a system named MapSense is proposed based on two critical observations in conventional fingerprint-based positioning systems. First, the RSS observations used in both site survey and positioning stages are readings of absolute values. However, the MHs involved in either stage are usually different in hardware, and the MHs are held in the different orientation and places, such as on the hand or in the pocket. Both device diversity and usage diversity cause severe RSS variance, which is well-known practical concerns in real-world deployment [5]. The use of absolute RSS value could result in an inevitable error of positioning accuracy. Second, in site survey process the RSS observation is collected by an MH at each discrete reference points. To obtain best observations reflecting real RSS values, the user holding MH is usually in stationary and collecting many samples at each reference point. While in positioning process, the MH is in movement and RSS is observed by the MH in moving state. Movement causes fluctuation of RSS and much fewer samples at each location depending on the speed of movement, which leads to a massive error when comparing with RSS observations in

This work was supported in part by UK EPSRC Project NIRVANA (EP/L026031/1), EU H2020 Project iCIRRUS (GA-644526), U.K. EPSRC Project DANCER (EP/K002643/1), EU FP7 Projects CROWN (GA-2013-610524) and Natural Science Foundation of China (Grant No. 61620106011).

Xuan Du and Kun Yang are with the School of Computer Science and Electronic Engineering, University of Essex, Colchester CO4 3SQ, U.K. (e-mail: xdua@essex.ac.uk; kunyang@essex.ac.uk).

Dongdai Zhou is with the College of Software, Northeast Normal University, Changchun 130117, China (e-mail: ddzhou@nenu.edu.cn).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

site survey stage.

MapSense relies on one basic assumption that the indoor map describing the indoor environment is available. The assumption is made based on several considerations. First, with the development of IoT, Smart Cities, Ambient Assisted Living and so on, the location is a very useful context [6]. The widely-used Google Map for outdoors was just launched in 2005, and nowadays almost all the location-based services are based on Google Map or similar platforms [7], [8]. Thus, we believe the indoor map will continually be available in most indoor places soon. Second, the map is an essential prerequisite to support tracking or navigation services, which has been proved by outdoor in-car navigation [9]. The indoor map system will eventually be built up although the development of it is in early stage and facing many difficulties. Third, in the last decade, researchers proposed many indoor positioning solutions by collecting and fusing various data, including different RF signals, the inertial sensor, acoustic data, vision data and indoor map. Among those data, apart from the indoor map the availability and quality of them dependent on the positioning technology. However, compared with other data, the indoor map is always available and can work with any positioning technology [10]. In conclusion, we believe the indoor map is a key component to bring indoor positioning into practice so it's very worthy of investigation.

In summary, the major contributions of this paper are as follows.

- The WiFi signal observations under modern enterprise WiFi infrastructure are analysed, and WiFi sibling signal pattern is defined for the first time and processed to generate Beacon APs which have higher confidence in positioning.
- An indoor pathway map is introduced and path segments are intensively utilised. The feature of spatial signal patterns over pathway map is used to reduce the search space during location estimation.
- A positioning approach using Beacon AP and signal coverage constraint is proposed to reduce the influence of signal RSS fluctuation and eventually improve the positioning accuracy.

This paper is organised as follows. Section II discusses the related work in literature and signal patterns in particular. In Section III, the analysis of WiFi signal observations is presented and sibling signal pattern is defined. The indoor pathway map and WiFi signal collected on pathway map are given in Section IV. The algorithm of Beacon AP generation is provided in Section V. The Beacon AP is mapped to pathway map and the concept of signal coverage constraint is discussed in Section VI. The positioning schemes using Beacon AP and signal coverage constraint is presented in Section VII. Performance evaluation and analysis of the proposed scheme are reported in Section VIII before the paper concludes in Section IX.

II. Related Work

This section presents a brief overview of recent works on indoor positioning and discusses several works utilising signal patterns. The approaches used for WiFi-based positioning can be classified into two categories, range measurement and fingerprinting. Both methods are facing numerous challenges to achieve their expected performance for indoor positioning [11]. In the two approaches mentioned above, they require the targeted device to participate in the positioning work. There are also some other positioning approaches without the involvement of targeted device, which is named device-free passive positioning [12].

A. Technologies and Performance

The positioning performance needs to be evaluated in real-world experiments, and there are different possible factors for the various accuracy. The accuracy can be affected under different environments with possible factors including furniture setup, building structure, people density and the evaluation locations. There are several metrics used to evaluate the accuracy, such as CDF (Cumulative Distribution Function) accuracy in certain percentile or average location error. Previous study [3] has revealed that the metrics and evaluation process of todays indoor positioning system are not well defined to consider the variations in the real world. The different positioning approaches also have the distinct robustness of the environment changes. The Microsoft competition introduced in [3] discusses the influence of different environments, which is the reason to organise the competition under the same environment. Thus, more standardisation of accuracy and evaluation is needed to be conducted.

RSS is the most commonly used signal feature for positioning, which reflects the distance between transmitter and receiver, but wireless signals often propagate via multiple paths in a dynamic indoor environment, which leads to unpredictable RSS fluctuations. Thus, the accuracy of RSS-based positioning is decreased mainly because of inconsistent RSS signals [13]. Recent years have seen the channel state information (CSI) as the signal feature of a location [14]. CSI is an emerging technique to replace RSS information. Compared with RSS, which is only a single-value MAC (Media Access Control) layer information, CSI is obtained from the PHY (Physical) layer and provide more information that represents the multi-path propagation. CSI describes how a signal propagates from the transmitter to the receiver and reveals the effect of multi-path. Finer-grained and more robust signal features can be extracted from CSI. CSI can work with either range measurement or fingerprinting technique. However, compared with RSS that is easy to be obtained in most mobile devices by calling the API of the operating system, CSI is not available in most mobile device platforms such as Android and iOS, and more importantly, CSI brings high computation complexity [15].

B. Signal Patterns

The main problem leading to insufficient positioning accuracy is the inconsistent WiFi signals, which is caused by signal fluctuation, changes in the indoor environment and mobile device heterogeneity. Thus, in recent years various solutions are proposed to mitigate the influence of inconsistent WiFi

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

signals. If only considering the signal samples collected at a single location and time, some approaches using statistics of RSS to address the RSS instability are proposed [16]. Otherwise, observing the signals from a broader view (such as from a spatial or temporal point of view) to generate patterns can help improve positioning accuracy [2]. The discovery and usage of several signal pattern are discussed as follows.

Even though in the fingerprinting-based positioning system the RSS values are broadly used as the metric of fingerprint and not used to calculate the distance between the receiver and AP, the RSS values still correlate to the location of APs. As the APs are usually scattered in the indoor environment, the novel RSS values measured at specific area can be used as the WiFi landmarks to identify this area uniquely. These WiFi landmarks can be discovered when the site survey is finished and the RSS measurements of the whole site are available. Inspired by such observation, people are investigating the patterns of WiFi signals from the spatial aspect, which is called spatial signal pattern.

Initially, the spatial patterns of individual APs are investigated and used to correct or constrain the location estimation, which typically needs to work with motion information from inertial sensors and may not always be available since the APs are not densely deployed to form sufficient landmarks [17]. Later on, the spatial patterns of multiple APs are considered to investigate more reliable approaches. The order of RSS values from different APs is used in HALLWAY [18] as a location-dependent measurement to distinguish the rooms, which can reduce the influence of various mobile devices and signal fluctuation. The effectiveness of the order of RSS values depends on the use scenarios and indoor floor plan because the granularity of its location estimation is limited to a certain level and if the rooms are too small, the adjacent rooms cannot be discriminated. Except for the order of RSS values, another approach to mitigating the measurement uncertainty is to identify the target location using a range of RSS values rather than the absolute RSS values. Based on this observation, Sectjuntion [19] is proposed to partition the coverage of each AP to sectors according to discrete signal levels from the location where the AP shows maximum RSS value. The RSS sector calculation is conducted after the site survey is completed and takes the RSS measurements at RPs of the whole site into the calculation. The APs with a narrow range of RSS observations are filtered out for RSS sector calculation because it discriminates fewer sectors. Finally, the target location is estimated using the intersection of the sectors from multiple APs. The spatial signal pattern can help narrow down the search space and reduce the maximum error distance (i.e., in the positioning process to prevent the search space being a dispersed set of RPs, which are quite distant apart geographically).

Observing the signal pattern for a continuous period to investigate the temporal signal patterns is also an approach widely adopted. Kim et al. [5] propose a smartphone-based pedestrian-tracking system using WiFi, which utilises both spatial and temporal signal patterns. They deeply investigate the inconsistent RSS problem, and their analysis shows that fingerprint-based indoor tracking suffers significant performance degradation due to the RSS variance, while the positioning of a stationary location is more robust to the RSS variance. In their system, an approach named Peak-based WiFi Fingerprinting (PWF) is proposed to overcome the inconsistent RSS problem. In the site survey the RSS vectors at different locations are collected as the traditional fingerprinting system, then the locations with maximum RSS of each AP are selected and recorded with the maximum RSS values. In the tracking phase, the peak RSS is detected from a sequence of observed RSS values and compared with the maximum RSS value recorded in the site survey. If the RSS value difference between the observed peak and recorded maximum value is less than a predefined threshold, the location with the detected peak is determined as the estimated location. Because RSS peak locations are limited and PWF has only about 20% occurrence ratio, other schemes such as traditional KNN method are used in the positioning in other areas. The PWF method improves the system accuracy by detecting the signal strength peak from temporal signal patterns but has the problem of potential missing scan of peak values. Walkie-Markie [20] is a system that aims to generate the map of indoor pathway using the WiFi signal and IMU data crowd-sourced from multiple mobile phone users. The WiFi-defined landmark (WiFi-Mark) is introduced in Walkie-Markie to act as the anchor to merge large volume of partial trajectories and limit the drift of IMU-based tracking. WiFi-Mark is defined as a location where the trend of an APs RSS reverses, i.e., as the user moves along a pathway, the RSS reading is changing from increasing to decreasing. This approach by examining the RSS trend instead of RSS readings turns out that no matter how the devices are different and how the user is holding the device, the WiFi-Mark occurs at the same location, which shows the effectiveness of temporal signal patterns.

C. Research Gaps

In summary, the spatial signal patterns can help reduce the problems caused by signal fluctuation and improve the positioning accuracy. However, the signal patterns only work well under a specific area of an indoor floor plan. Meanwhile, the site survey needs accommodate the required approach of collecting signals, and these signals need to be processed to generate the features of signal patterns. Thus, in this paper, the information of indoor map is used to assist the discovery and usage of signal patterns in both site survey and positioning to achieve better accuracy and efficiency.

The only work in the literature utilised the virtual AP feature for positioning is [21], where they mentioned that averaging the RSS values of signals from the same physical AP over time can obtain more stable RSS values. However, they failed to provide details about how the signal observations are processed to identify the virtual APs and afterwards used for positioning. This work will investigate the ubiquitous signals from sibling APs under enterprise WiFi infrastructure for positioning.

III. Analysis of WiFi Signal Observations

To decide how to use the WiFi signals efficiently and adequately, analysing WiFi signals is conducted in our ex-

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

perimental site, i.e., central campus building at University of Essex Colchester Campus. Each single AP is uniquely identified by the Basic Service Set Identifier (BSSID). Around 200 APs are observed during the 25 seconds' movement, i.e., a walking trajectory, rather than at a single location. The Fig. 1 (left) pie chart shows the percentage of observed APs with different appearance frequency (denoted by N) when a mobile handheld is moving along a corridor for 25 seconds. With the increase of appearance frequency, the number of APs decreases significantly. Around one-third of APs are observed only once and about a quarter of APs are observed for more than three times. The AP appearing fewer times means its signal strength typically are weak and it can be observed only within a short period. The Fig. 1 (right) bar chart shows the distribution of observed APs in 2.4 GHz and 5 GHz frequency band respectively. APs of 5 GHz dominates the observations with smallest and largest appearance frequency, which reveals that 5 GHz channels may be less crowded and weak signals in 5 GHz are more likely to be observed than that in 2.4 GHz [22].

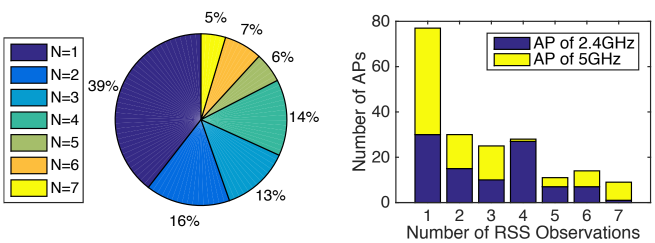


Fig. 1. Occupancy of 195 observed APs with a different number of observation (left) and frequency band (right).

Through empirical investigation of the WiFi networks in our experimental site, one primary reason caused the excessive number of APs is the virtual access point (VAP) functionality of enterprise WLAN infrastructure, which allows one physical AP to have multiple separate WLAN with its BSSID and SSID (service set identifier). Another reason is the AP's Simultaneous Dual-Band functionality that enables each WLAN to operate in both 2.4 GHz and 5 GHz frequency band, which uses two different BSSID but the same SSID. In this paper, we name the APs from the same physical AP as **sibling APs**.

The idea of fingerprint-based positioning was initially proposed based on the principle that several APs located at different places can provide different signal strength observations in different observation point. However, nowadays the APs observed by users are heterogeneous, and some of them are coming from the same physical AP at the same location. Thus, the concept of **sibling signal patterns** (SSP) is proposed to describe the correlation between the sibling APs.

The sibling signal patterns are investigated in our work. Since the VAPs from the same physical AP share the same radio frequency, which has been verified in our experiment, we believe the signals of these VAPs suffer similar interference in the environment and the RSS of them at the same place are supposed to be the same. This thought is proved by the real data collected in our experiment, which is depicted in the Fig. 2. The top and bottom bar chart in the Fig. 2 respectively shows the time-series RSS observations of VAPs operating in both 2.4 GHz and 5 GHz frequency band, which are observed by a mobile device moving along a corridor for 25 seconds. In total, there are 9 BSSID coming from the same physical AP. The bar charts illustrate that the RSS of VAPs coming from the same physical AP and operating in the same frequency band are almost identical at the same time and location. Apart from fluctuation caused by noisy environment, the minor difference of RSS between VAPs may also come from the measurement tolerance in the mobile device. At certain locations, the APs with weak signals are not observed. In general, the observations in 5 GHz has better integrity than that in 2.4 GHz.

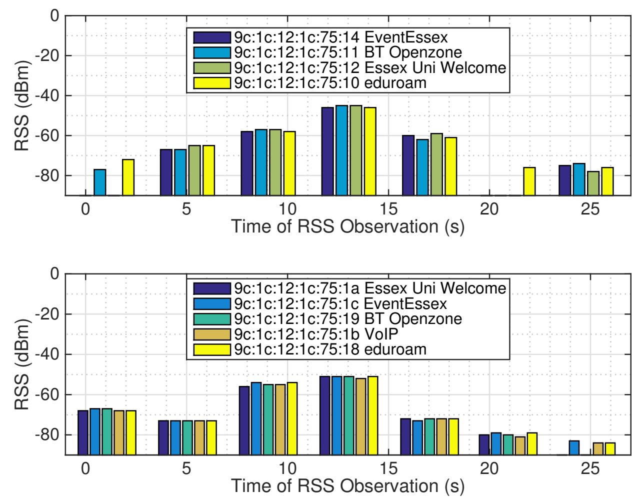


Fig. 2. The RSS observations of VAPs operating in 2.4 GHz (top) and 5 GHz (bottom) frequency band from the same physical AP when moving along a corridor for 25 seconds.

IV. Pathway Map

A. *Introduction of Pathway Map*

Like the outdoor map in which the road is the skeleton, and the points of interests (PoI) are referenced by road name and number, we believe in the indoor space the pathway is the vital part of the indoor map, and most indoor activities are related to people's movement along the pathway.

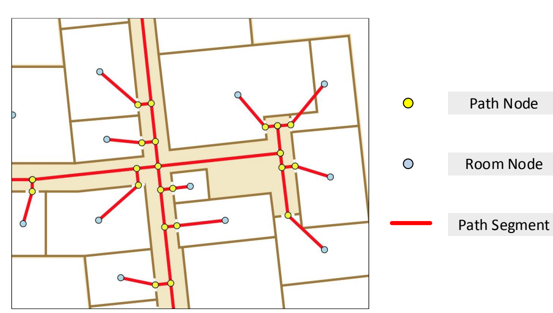


Fig. 3. Illustration of pathway map.

The data of indoor map is structured by the Scalable Vector Graphic (SVG) format and contains the polygons representing

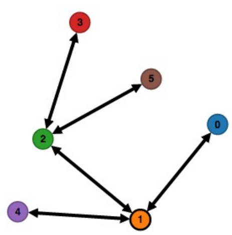
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

rooms' outline, coordinates of rooms' door and polylines indicating the corridors. Based on these data the pathway map is generated to represent the available indoor walking routes between rooms, i.e., the possible path people may move along. Fig. 3 shows the structure of pathway map. Pathway map is depicted in diagrammatic form as a set of dots for the nodes, joined by lines for the path segments. The nodes are constituted by path nodes and room nodes. Path nodes and room nodes are represented by its ID and its coordinates are stored in a table of nodes entries. Each path segment is directed and expressed by its start node ID, end node ID, length and type.

B. Data Structure of Pathway Map

The pathway map is $G = (V, E)$, where V is a non-empty set of nodes and E is a set of ordered pairs of these nodes to represent path segments. A path segment $e \in E \subset V \times V$, where $e = (u, v)$ and $u, v \in V$. A path segment (u, v) is considered to be directed from u to v, where u is start node and v is end node.

The data of nodes are stored as an array, and the path segments are stored as an adjacency matrix to represent the connectivity between nodes. As the illustration in Fig. 4, a pathway map with n nodes $\{v_1, v_2, \ldots v_n\}$ can be represented by an $n \times n$ adjacency matrix A, in which a_ij is the number of path segments joining v_i and v_j. As the path segment is directed, in the adjacency matrix the entry in the row is the start node, and the entry in the column is the end node.



	v_0	v_1	v_2	v_3	v_4	v_5
v_0	0	1	0	0	0	0
v_1	1	0	1	0	1	0
v_2	0	1	0	1	0	1
v_3	0	0	1	0	0	0
v_4	0	1	0	0	0	0
v_5	0	0	1	0	0	0

Fig. 4. Illustration of pathway's nodes and its adjacency matrix representing the connectivity between nodes.

C. WiFi Signal Collected on Pathway Map

TABLE I
PART OF THE NOTATIONS.

Notation	Description
G	A pathway map
v	A node in the pathway map
e	A path segment
$\mathbf{S}_i$	RSS values observed from e_i
$\mathbf{T}_i$	Observation timestamps from e_i
K	Number of APs
N	Number of observations
$\mathbf{x}_k$	RSS values from k^{th} AP
x_n	RSS value of the n^{th} observation
b_k	BSSID of k^{th} AP
f_k	Frequency of k^{th} AP

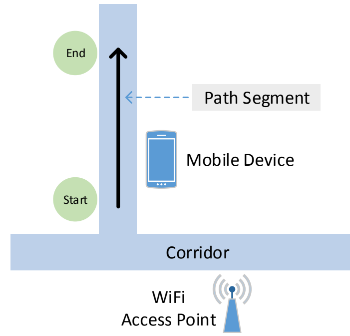


Fig. 5. Illustration of a path segment where the WiFi signals are collected.

A path segment is a directed line segment consisting of a sequence of points in the corridor and defined by a start node and an end node, as illustrated in Fig. 5. When the mobile handheld of a surveyor is moving along a path segment, a set of continuously observed raw RSS from surrounding APs are collected.

The RSS observation collected at path segment e_i from K number of APs is denoted as

$$\mathbf{S}_i \equiv (\mathbf{x}_1, ..., \mathbf{x}_K), \tag{1}$$

where $\mathbf{x}$ denotes a vector of time-series RSS observation value x with size of N, which is denoted as

$$\mathbf{x} \equiv (x_1, ..., x_N)^{\mathbf{T}}. \tag{2}$$

The number of observations N can be different in $\mathbf{x}_k$ from different APs.

With the RSS observation $\mathbf{S}_i$, the corresponding observation timestamp of the RSS values are collected as well, which is denoted as

$$\mathbf{T}_i \equiv (\mathbf{t}_1, ..., \mathbf{t}_K), \mathbf{t} \equiv (t_1, ..., t_N)^{\mathbf{T}} \tag{3}$$

Meanwhile the BSSID and frequency of APs are also recorded and denoted as

$$\mathbf{b} \equiv (b_1, ..., b_K)^{\mathbf{T}} \tag{4}$$

and

$$\mathbf{f} \equiv (f_1, ..., f_K)^{\mathbf{T}}. \tag{5}$$

V. BEACON AP GENERATION

A. Introduction of Beacon AP

The analysis of WiFi signals concludes that the overall quantity of available APs is massive and the appearance frequency of APs differs significantly. Using all the observed APs for positioning leads to high computation complexity and may cause additional errors. Thus, the overall quantity of APs need to be reduced, and quality of APs needs to be evaluated and filtered. Eventually, only a small portion of high-quality WiFi signals are used for positioning.

The analysis reveals that the VAPs from the same physical AP present similar observed RSS. Thus, the concept of **Beacon AP** is proposed and a Beacon AP is defined as a delegation to the VAPs from the same physical AP and in the same frequency. The fingerprints of Beacon APs are finally saved into fingerprint database and used for positioning.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

B. Beacon AP Generation Algorithm

Algorithm 1 Beacon AP Generation Algorithm

Input: $\mathbf{S}, \mathbf{T}, \mathbf{b}, \mathbf{f}$
Output: $\mathbf{W}$ - RSS values of Beacon APs.

// Step 1: remove APs appearing few times.
$Max \leftarrow$ maximum size of $\mathbf{x}_k$ in $\mathbf{S}$.
for each $\mathbf{x}_k \in \mathbf{S}$ **do**
  if $sizeof(\mathbf{x}_k) < Max \times 0.7$ **then**
    remove $\mathbf{x}_k$ from $\mathbf{S}$
  end if
end for
// Step 2: group remaining APs by frequency.
$q \leftarrow$ number of different frequency appeared in $\mathbf{f}$.
$\mathbf{v} \leftarrow$ a vector of size q to store the unique frequencies.
$\mathbf{M} \leftarrow$ initialize q number of groups.
for each $\mathbf{x}_k \in \mathbf{S}$ **do**
  add $\mathbf{x}_k$ to group $\mathbf{m}_q$ where $f_k == v_q$
end for
// Step 3: cluster the VAPs in each frequency group.
for each $\mathbf{m}_q \in \mathbf{M}$ **do**
  $\mathbf{r} \leftarrow$ initialize a vector of size k.
  $r_k \leftarrow b_k$ without last 4 bits.
  $\mathbf{D} \leftarrow$ cluster $\mathbf{x}_k$ of the same r_k
  for each $\mathbf{d} \in \mathbf{D}$ **do**
    $u_{k,l} \leftarrow$ Euclidean distance between $\mathbf{x}_k$ and $\mathbf{x}_l$
    if $u_{k,l} > Et \ \& \ sizeof(d) > 2$ **then**
      $\mathbf{C} \leftarrow$ add cluster $\mathbf{d}$ into $\mathbf{C}$
    end if
  end for
end for
// Step 4: generate Beacon AP of each cluster.
$p \leftarrow sizeof(\mathbf{C})$
$\mathbf{W} \leftarrow$ initialize to store RSS values of Beacon APs.
for each $\mathbf{c}_p \in \mathbf{C}$ **do**
  $\mathbf{s}_n \leftarrow$ add x_n which has less than 1s difference in t_n
  $w_{pn} \leftarrow mean(\mathbf{s}_n)$
end for
return W

The steps to generate Beacon APs using sibling signal patterns are as the pseudocode in Algorithm 1. The Beacon AP generation algorithm takes the raw observations of WiFi signals from each path segment as input and generates Beacon APs of the path segment as output. Firstly, considering strong signal (i.e., signals with large RSS value) shows higher confidence than weak ones and APs appearing fewer times are relatively weak. Therefore APs with low appearance frequency are filtered out. A threshold indicating appearance frequency is used to control the APs which need to be removed. Secondly, the remaining APs are divided into groups by their frequency. Each group may contain APs of the same frequency but from more than one physical APs because more than one APs may operate at the same frequency. Thus, thirdly, the APs in each group are grouped again to form the cluster of APs which are at the same frequency and from the same physical AP, i.e., the VAPs from a physical AP. The approach to cluster the VAPs is based on empirical practice and theoretical verification. Finally, each VAP cluster is processed to generate a Beacon AP. The processed observation of signals in different stages are illustrated in Fig. 6 using one path segment of our experimental site as an example.

C. Clustering VAPs

The empirical practice is that the BSSID of VAPs from the same physical AP normally has a certain correlation. The MAC address of AP is usually used as the BSSID and contains 48 bits. The MAC addresses of VAPs in the same physical AP are usually the same except last 4 bits. Thus, VAP key is defined as $\{BSSID[1:44], Frequency\}$, for example, {24:de:c6:c3:5b:b, 2412}. The VAPs are identified and clustered based on their keys. To make sure the empirical practice always work correctly, the clustered VAPs are verified by checking the similarity between signal patterns. The similarity between temporal signal patterns from two APs is determined based on the Euclidean distance between them, which is denoted as

$$u_{kl} = \sqrt{\sum_{m=1}^{M} \{\mathbf{x}_{k,m} - \mathbf{x}_{l,m}\}^2} \tag{6}$$

where M is the number of RSS observations in which both APs appear at the same timestamp and in the same channel. If the Euclidean distance between any two APs in the cluster is larger than the threshold, the VAPs in this cluster may not be from the same physical AP, and this cluster is abandoned and not used for the further process.

D. Beacon AP Finalisation

Before the clustered VAPs are used to generate Beacon AP, the number of VAPs in each cluster is checked against a threshold, and if it is too few, we can believe the VAPs in this cluster have fewer opportunities to be spotted. Our experiment also shows the VAPs in the cluster of small size have relatively weak signal strength. Thus, only the clusters with more than two VAPs are kept to generate Beacon APs. Finally, in each cluster, if the observations of different VAPs are captured in the same time, the mean of their RSS values is computed and used as the RSS value of Beacon AP at that timestamp, which is then used to construct the RSS map (i.e., fingerprint database) for positioning.

VI. Beacon AP over Pathway Map

A. Construction of Beacon AP RSS Map

To map the signal observations to the spatial locations, the reference points are employed like most fingerprint-based approaches. However, the RPs proposed in our work are closely associated with pathway map, and the nearby RPs can easily be identified, which can ease the prediction and reduce the searching space if needed in the positioning phase. Each RP's identity is coded as $[P.S.I]$, where P is the ID of path segment where the RP exists, S is the number of RPs existing in this path segment, and I is the sequential number of this

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

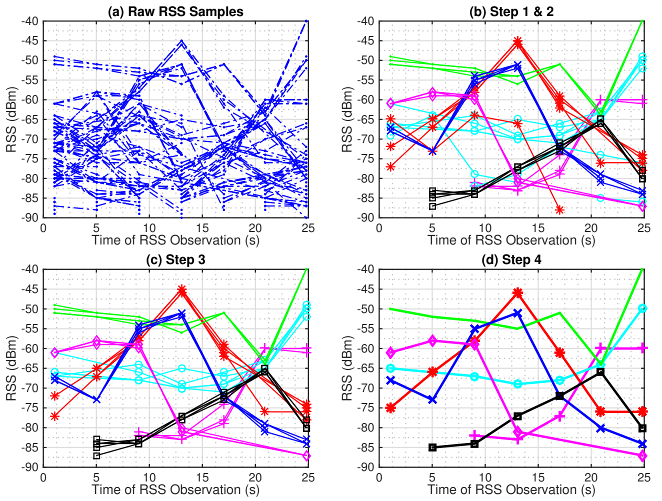


Fig. 6. Illustration of processing signal patterns from raw RSS samples observed from APs in one path segment of our experimental site.

RP in S. For example, RP [238.5.2] and [238.5.3] are adjacent to each other. Furthermore, RPs from adjacent path segments can also be retrieved by querying the pathway map.

The RSS of Beacon APs processed from raw signal observations are mapped to the indoor map to form RSS map of Beacon APs. The RSS map consists of RSS from Beacon APs at RPs of each path segments. The RSS from P number of Beacon APs at N number of RPs of path segment e_i is denoted as

$$W_i = \begin{pmatrix} w_{1,1} & \cdots & w_{1,N} \\ \vdots & \ddots & \vdots \\ w_{P,1} & \cdots & w_{P,N} \end{pmatrix} \tag{7}$$

where $w_{pn} = -100$ if Beacon AP p is not observed at RP n, because the weakest signal observed is close to -100 but not less than -100. Because in the Beacon AP generation algorithm the APs appearing few times in the path segment have been removed, we believe the Beacon AP can be seen in the path segment for most of the time. The number of RPs of each path segment is determined based on its length. Since Beacon APs are elected based on path segment and just represent signal patterns over that path segment, size and identity of Beacon APs in different path segments are not consistent.

B. Signal Coverage Constraint

By processing the raw signal observations using sibling signal pattern, the Beacon APs are generated as quality-improved metrics to represent the surrounding signal measurements along path segments. The same Beacon AP may appear in different path segments, most probably in adjacent path segments. The number of RPs of each path segment is determined based on the length of path segment and walking speed of the surveyor in the process of the site survey. The number of Beacon APs depends on the number of available raw APs and length of the path segment. At our experimental site about 7-10 Beacon APs are elected in a path segment of 10 meters' length. The Fig. 7 illustrates the distribution of beacon APs' appearance in the RPs using some of our experimental samples in a two-dimension scatter diagram, where the AP with RSS of -100 (i.e., AP unobserved) is not shown to reveal the real-world observations. As the illustration in the Fig. 7, there are 41 RPs in the 4 continuous path segments and 28 Beacon APs in total are elected over these path segments. Each Beacon AP is typically shown in a group of continuous RPs, which can take up one or two adjacent path segments. The geographical distribution of RPs from the same Beacon AP shows strong aggregation. Thus, the spatial patterns of multiple Beacon APs can be used to constrain the searching space of user's location.

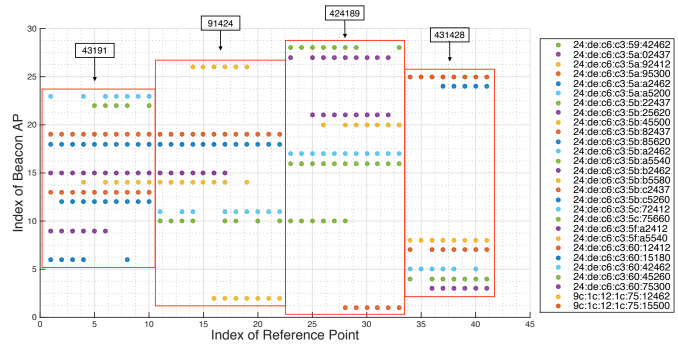


Fig. 7. Illustration of mapping Beacon APs to reference points based on the signals collected at our experimental site.

To obtain a better visualised insight of the spatial signal pattern, the Fig. 8 illustrates the geographic mapping between beacon APs' appearance and pathway map using the signal observations collected over several continuous path segments in our experimental site. Based on spatial signal pattern, the concept of **signal coverage constraint** (SCC) is proposed. The signal coverage constraint is intended to check if the current observed Beacon APs match the Beacon APs elected for each path segment in the fingerprint database. Through signal coverage constraint the user's potential location can be limited to one specific path segment, or more than one in some cases when the Beacon APs of more than one path segment are similar and all match the current observation. The approach we define the match is that the Beacon APs of current observation can take up that of the path segment for more than a threshold, which is signal coverage constraint ratio (SCC ratio). For example, when SCC ratio is 80%, if 8 out of 10 Beacon APs of a path segment are shown as Beacon APs of current observation, then this path segment is considered as the area of users' potential location. In such approach, the search space can be reduced to a small area consisting of the RPs of this path segment.

VII. Positioning using Beacon AP and Signal Coverage Constraint

The system consists of three modules: site survey, SSP processing and positioning, as the system architecture depicted in Fig. 9. In the offline phase, a dedicated surveyor holding an MH running site survey module is walking along the corridors to collect raw observations. Then the server-side SSP Processing module processes the collected raw data to produce

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

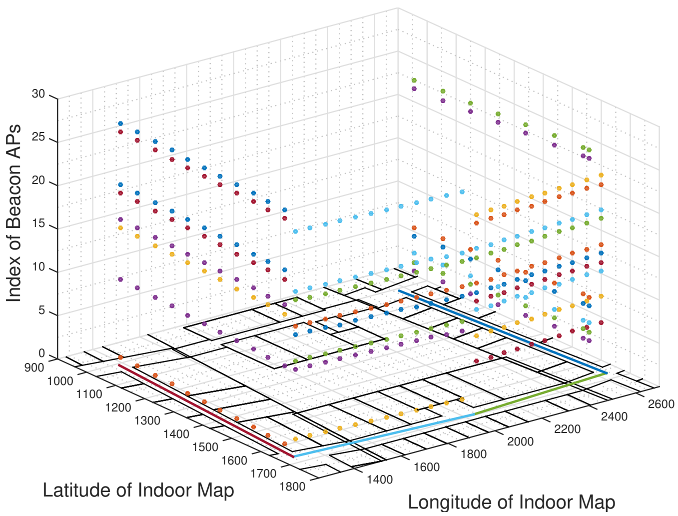


Fig. 8. Illustration of mapping Beacon APs to pathway map based on the signals collected at our experimental site.

Beacon AP RSS map. In the online phase, positioning module is running on the targeted MH to observe the real-time signal and compare it with the Beacon AP RSS map in the database to compute the location of the MH.

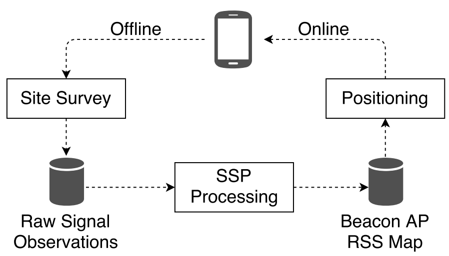


Fig. 9. System Architecture.

A. Robust Searching Scheme

In the robust searching scheme, the search space is the RSS map of the whole site, consisting of all the reference points over the path segments. All the RPs are candidate RPs and the similarity between the fingerprint of RP and the real-time measurement is the Euclidean distance between the RSS vectors of all the APs shown at the RP. If any AP is not shown in the real-time measurement, the RSS value of -100 is given to the AP. The K-Nearest Neighbors (KNN) algorithm is used to find the best-matched fingerprint of RPs where K=1, and the location of the best-matched RP is the estimated location.

B. Selective Searching Scheme

A massive search space can lead to not only dispersed positioning results but also very high computation cost. Thus, inspired by spatial signal pattern, a selective searching scheme is introduced by adding the signal coverage constraint function to the robust searching algorithm. In the selective searching scheme, the candidate RPs are selected by checking the APs' signal coverage, which narrows down the search space. For each path segment in the RSS map, the mutual APs appeared in both the path segment and current observation are obtained. The number of mutual APs is checked against the total number of APs of this path segment because the path segment is possible to be the estimated location only when most of the APs in the path segment are present. The selective searching scheme works as the pseudocode in Algorithm 2.

Algorithm 2 Selective Searching Algorithm

Input:
h_0 - RSS observation values;
W - RSS map;
r - SCC ratio.
Output:
L - coordinate of user's location.

$\mathbf{a} \leftarrow$ get all the APs of h_0
$\mathbf{e} \leftarrow$ initialize an array to save similarity to each $\mathbf{x}_k$
for each $\mathbf{x}_k \in W$ **do**
  $\mathbf{b} \leftarrow$ get all the APs of $\mathbf{x}_k$
  $n \leftarrow$ get number of APs in $\mathbf{a}$
  $\mathbf{c} = \mathbf{a} \cap \mathbf{b}$
  if $sizeof(\mathbf{c})/sizeof(\mathbf{b}) > r$ **then**
    $e_o \leftarrow$ calculate Euclidean distance between $\mathbf{x}_k(\mathbf{c})$ and $\mathbf{h}_0(\mathbf{c})$
    $e_k \leftarrow e_o/sizeof(\mathbf{c})$
  end if
end for
$L \leftarrow$ get location of $x_{min(\mathbf{e})}$
return L

The selective searching algorithm takes current RSS observation and RSS map as inputs and outputs the estimated location. The SCC ratio is used to control the proportion of mutual APs. If the path segment passes the SCC ratio check, the RPs of the path segment becomes candidate RP and the Euclidean distance between the RSS vectors from mutual APs is calculated. The Euclidean distance divided by the number of mutual APs is used as the similarity between the RP and current observation. Finally, the candidate RP of smallest similarity value is elected as the estimated location.

VIII. Evaluation

A. Experimental Setup

We develop the prototype in which the site survey and positioning modules are implemented on Android platform and the Beacon AP generation module on Matlab. All the data collected on Android smartphone are saved into SQLite database, which is retrieved by Matlab to process and then send back to the smartphone to eventually fulfil positioning. The experiments are conducted on the 5th floor of the central campus building at the University of Essex Colchester Campus, which is about 50 meters' length, as depicted in Fig. 10. Since the positioning performance of movement in corridors is our main concern and corridors are just all accessible area, the office or seminar rooms are not covered in our experiment. The experimental site is covered by signals from about 50 wireless APs (250 VAPs) of Aruba which belongs to the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

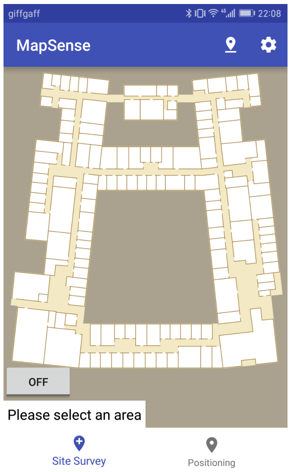


Fig. 10. Illustration of the indoor map of the experimental site.

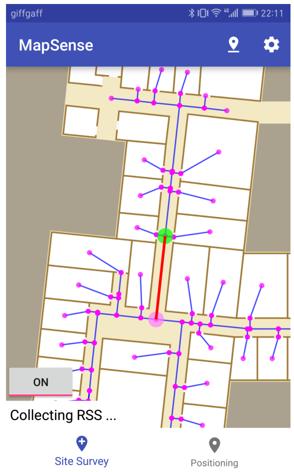


Fig. 11. Illustration of the user interface of site survey.

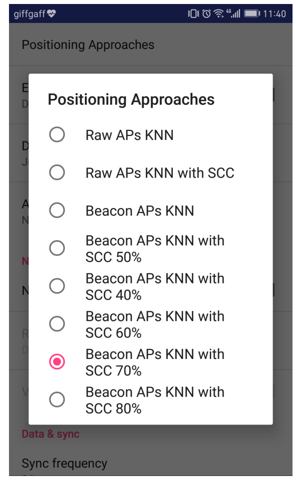


Fig. 12. Illustration of positioning scheme selection.

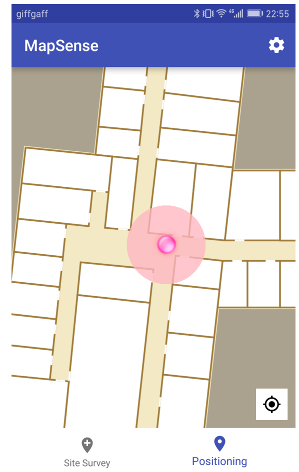


Fig. 13. Illustration of the positioning result shown on Android app.

campus WiFi infrastructure mounted on the ceiling. In other words, the APs observed and used for positioning in this paper are existing and deployed by the university to provide the Internet access, rather than deployed explicitly for experiments of indoor positioning. Empirically speaking, there are around two-thirds of APs deployed in the six-floor building where the experiments are c, and the other one-third of APs are from other surrounding buildings.

The performance of the work in this paper is evaluated from two aspects, positioning accuracy and energy efficiency. The benchmark is the raw AP RSS approach used by most systems nowadays. The proposed work of this paper, Beacon AP and Spatial Signal Constraint, are deeply evaluated by comparing with the raw AP RSS approach. Because the different positioning approaches need to be evaluated in the same environment and evaluation points, the benchmark approach and proposed schemes are implemented and evaluated under the same condition. The different positioning schemes are implemented in the Android app and allow users to select on the setting menu. In raw RSS scheme, reference points are sampled approximately every 3-5 meters, and each RP is trained for around 10 seconds. In the Beacon AP RSS scheme involving sibling signal patterns, the environment is profiled by site survey at a steady speed (about 1 meter per second), as shown in Fig. 10. The user interface of the site survey service running on a mobile phone is shown as Fig. 11. In the positioning stage, no matter what scheme is applied, the positioning result is shown as a red dot on the map, as shown in Fig. 13. To evaluate the accuracy, ground truth is marked by tapping the real location on the map and saved into positioning logs. Location error is defined as the Euclidean distance from the estimated location to ground truth. Meanwhile, some other data such as real-time observed APs and candidate RPs in positioning algorithm are also recorded into positioning log sat in SQLite database.

B. Effectiveness of Beacon APs

As the RSS variance is a significant problem of WiFi-based positioning, the effectiveness of sibling signal pattern is evaluated against different device setups. As described in Table II, two devices with different physical setup and software setting are employed to evaluate positioning performance while the site survey is conducted by Huawei P9. As shown in Fig. 14, in this test Beacon AP RSS leads raw RSS in the overall performance. Beacon AP RSS scheme provides positioning result within 2 meters from the ground truth in over 90%. The maximum location error distance is reduced by 2 meters to just over 3 meters against raw RSS scheme. The critical point is how two different schemes are affected in M4 setup. Based on raw RSS the location error is amplified when the MH running positioning module is not the MH performed the site survey. Under such situation using Beacon AP RSS, the positioning accuracy is also affected, but just a small drop, which reveals Beacon APs generated by sibling signal patterns are more robust to device variance.

TABLE II
DEVICE SETUPS

Setup	Device Model	Platform Version	WiFi Scan Frequency
P9	Huawei P9	Android 6.0	every 4s
M4	Xiaomi 4	Android 5.0	every 6s

Since the Beacon APs are generated based on RSS observations collected in the movement while the raw RSSs are collected in the stationary, the positioning accuracy is evaluated in both stationary and moving state. As illustrated in Fig. 15, Beacon AP RSS scheme offers the best performance when the MH is in movement. When the Beacon AP RSS scheme is used in the stationary, the performance decreases a bit, and its maximum error distance overtakes raw RSS scheme in the stationary. We believe the Beacon AP RSS scheme performs better in the movement because the Beacon APs and their RSSs are generated from RSS observations in the movement. While the raw RSS scheme in the movement performs worst. From which we can see Beacon AP RSS scheme are more suitable for application scenarios of moving MH.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

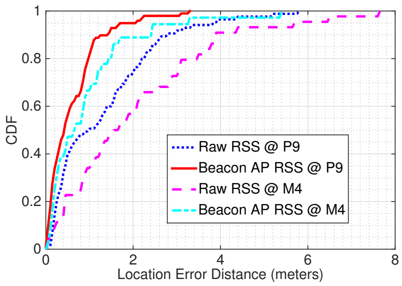


Fig. 14. CDF of location error distance using different device setups.

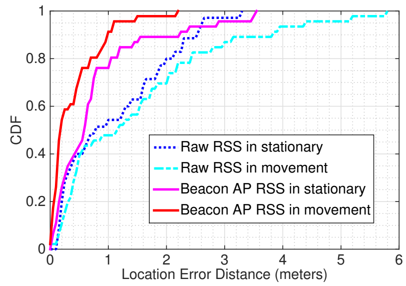


Fig. 15. CDF of location error distance in different usage scenarios.

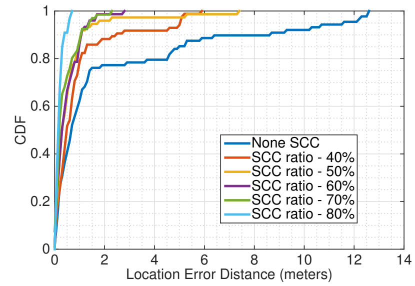


Fig. 16. CDF of location error distance using different SCC ratio in selective searching scheme.

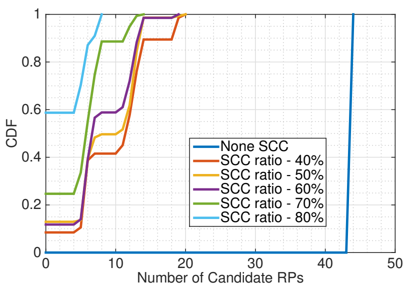


Fig. 17. CDF of number of candidate RPs using different SCC ratio in selective searching scheme.

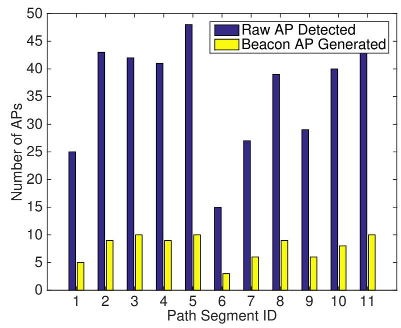


Fig. 18. Plot of bar chart showing the number of APs of raw APs detected and Beacon APs generated at some of path segments in the experimental site in offline site survey.

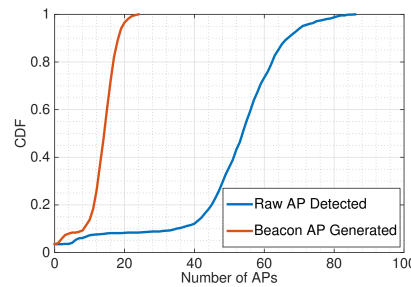


Fig. 19. CDF of the number of candidate RPs from positioning log.

C. Effectiveness of Signal Coverage Constraint

The selective searching scheme utilizes the signal coverage of APs to narrow down the search space by filtering the candidate RPs through the SCC ratio. To evaluate the effectiveness of signal coverage constraint and the influence of different SCC ratio, experiments of robust searching scheme and selective searching scheme using different SCC ratio are conducted. As the CDF shown in the Fig. 16, the robust searching scheme (i.e., none SCC) performs worst overall and with the maximum error distance of more than 12 meters. With signal coverage constraint, the accuracy is improved dramatically. Even though with SCC ratio of 40%, the maximum error distance is reduced to around 6 meters. With the increase of SCC ratio, the accuracy keeps increasing. When the SCC ratio is 80%, the accuracy is within 1 meter in all cases, which means the estimated location is always the nearest RP. The change of positioning accuracy affected by SCC reveals that constraining the estimated location through the signal coverage of APs can give the positioning accuracy huge boost, especially it can reduce the maximum error distance significantly.

The signal coverage constraint can improve the positioning accuracy massively, but it can lead to the problem that no candidate RP matches the online measurements, and hence no estimated location can be provided. In the positioning phase, for every location estimation job when the latest WiFi scan results are available, the number of measured APs, number of APs used in estimation and the candidate RPs are saved into logs. The Fig. 17 illustrates the CDF of the number of candidate RPs occurred when it is filtered using different SCC ratio. From which we can see that, with the increase of SCC ratio the probability that no candidate RPs are available is increasing at a growing pace. When the SCC ratio is 80% there is about 60% probability that no positioning result can be given. Thus, a trade-off between accuracy and availability is existing, and we think SCC ratio of 60% is the best choice.

D. Efficiency Comparison

Apart from positioning accuracy, the system efficiency is becoming another significant concern in the real-world deployment. In the site survey stage, the Beacon AP RSS approach can cover corridor of 20-meter length for less than 30 seconds. However, the traditional predefined RP iteration method can take more than 5 minutes depending on the grid size of RPs and sample size at each RP.

As the plot in Fig. 18, compared with the size of all raw APs detected, by using Beacon APs as the fingerprints of RPs the number of APs is reduced dramatically. At each path segment, the number of APs is only about one-fifth of all raw APs detected, which can reduce the dimension of fingerprint database significantly.

In the positioning stage, the RSS matching algorithm that calculates the similarity between RP and real-time RSS observation spends most computational resource and energy [23]. The computation cost of RSS matching algorithm mainly depends on the size of RSS vector (i.e., the number of APs) and the number of candidate RPs to search for the best-matched location. As shown in Fig. 19, the number of APs used for location estimation in the Beacon AP approach is

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2018.2797061, IEEE Internet of Things Journal

about 30% of that using raw AP. Using Beacon AP reduces the size of RSS vector to less than 20 in most cases. With the assistance of signal coverage constraint, the size of candidate RPs is also decreased significantly, as illustrated in Fig. 17. Beacon AP and SCC together reduce the computation cost dramatically.

IX. Conclusion And Future Work

In this paper, the sibling and spatial signal patterns are investigated. A positioning approach using Beacon APs and signal coverage constraint is proposed and shows better performance in both positioning accuracy and efficiency. In the experiments, for the path segment which is relatively short-distance, it has just a few number of RSS observations, in which case the Beacon AP cannot be generated, so other strategies like limiting the minimum length of path segment are necessary to be considered in the future work.

References

[1] X. Du, K. Yang, X. Lu, and X. Wei, "An indoor positioning approach using sibling signal patterns in enterprise wifi infrastructure," in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, June 2017, pp. 1728–1733.

[2] S. He and S. H. G. Chan, "Wi-fi fingerprint-based indoor positioning: Recent advances and comparisons," *IEEE Communications Surveys Tutorials*, vol. 18, no. 1, pp. 466–490, Firstquarter 2016.

[3] D. Lymberopoulos, J. Liu, X. Yang, R. R. Choudhury, V. Handziski, and S. Sen, "A realistic evaluation and comparison of indoor location technologies: Experiences and lessons learned," in *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*, ser. IPSN '15. New York, NY, USA: ACM, 2015, pp. 178–189. [Online]. Available: http://doi.acm.org/10.1145/2737095.2737726

[4] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *IEEE Transactions on Mobile Computing*, vol. 11, no. 12, pp. 1983–1993, Dec 2012.

[5] Y. Kim, H. Shin, Y. Chon, and H. Cha, "Smartphone-based wi-fi tracking system exploiting the rss peak to overcome the rss variance problem," *Pervasive Mob. Comput.*, vol. 9, no. 3, pp. 406–420, Jun. 2013.

[6] Y. Zhang, R. Yu, S. Xie, W. Yao, Y. Xiao, and M. Guizani, "Home m2m networks: Architectures, standards, and qos improvement," *IEEE Communications Magazine*, vol. 49, no. 4, pp. 44–52, April 2011.

[7] N. Vastardis and K. Yang, "Mobile social networks: Architectures, social properties, and key research challenges," *IEEE Communications Surveys Tutorials*, vol. 15, no. 3, pp. 1355–1371, Third 2013.

[8] Y. Cao, S. Yang, G. Min, X. Zhang, H. Song, O. Kaiwartya, and N. Aslam, "A cost-efficient communication framework for battery-switch-based electric vehicle charging," *IEEE Communications Magazine*, vol. 55, no. 5, pp. 162–169, May 2017.

[9] Y. Cao and N. Wang, "Toward efficient electric-vehicle charging using vanet-based information dissemination," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 4, pp. 2886–2901, April 2017.

[10] S. He, S. H. G. Chan, L. Yu, and N. Liu, "Fusing noisy fingerprints with distance bounds for indoor localization," in *2015 IEEE Conference on Computer Communications (INFOCOM)*, April 2015, pp. 2506–2514.

[11] C. Yang and H. rong Shao, "Wifi-based indoor positioning," *Communications Magazine, IEEE*, vol. 53, no. 3, pp. 150–157, March 2015.

[12] M. Youssef, M. Mah, and A. Agrawala, "Challenges: Device-free passive localization for wireless environments," in *Proceedings of the 13th Annual ACM International Conference on Mobile Computing and Networking*, ser. MobiCom '07. New York, NY, USA: ACM, 2007, pp. 222–229.

[13] X. Du and K. Yang, "A map-assisted wifi ap placement algorithm enabling mobile device's indoor positioning," *IEEE Systems Journal*, vol. 11, no. 3, pp. 1467–1475, Sept 2017.

[14] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti, "Spotfi: Decimeter level localization using wifi," in *Proceedings of the 2015 ACM Conference on Special Interest Group on Data Communication*, ser. SIGCOMM '15. New York, NY, USA: ACM, 2015, pp. 269–282.

[15] Y. Xie, Z. Li, and M. Li, "Precise power delay profiling with commodity wifi," in *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, ser. MobiCom '15. New York, NY, USA: ACM, 2015, pp. 53–64.

[16] S. Lee and M. N. Husen, "Recalibration-free indoor localization with wi-fi fingerprinting of invariant received signal strength," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct 2016, pp. 4649–4655.

[17] H. Wang, S. Sen, A. Elgohary, M. Farid, M. Youssef, and R. R. Choudhury, "No need to war-drive: Unsupervised indoor localization," in *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '12. New York, NY, USA: ACM, 2012, pp. 197–210.

[18] Y. Jiang, Y. Xiang, X. Pan, K. Li, Q. Lv, R. P. Dick, L. Shang, and M. Hannigan, "Hallway based automatic indoor floorplan construction using room fingerprints," in *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ser. UbiComp '13. New York, NY, USA: ACM, 2013, pp. 315–324.

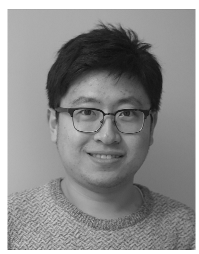
[19] S. He and S. H. G. Chan, "Sectjunction: Wi-fi indoor localization based on junction of signal sectors," in *2014 IEEE International Conference on Communications (ICC)*, June 2014, pp. 2605–2610.

[20] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang, "Walkie-markie: Indoor pathway mapping made easy," in *Proceedings of the 10th USENIX Conference on Networked Systems Design and Implementation*, ser. nsdi'13. Berkeley, CA, USA: USENIX Association, 2013, pp. 85–98.

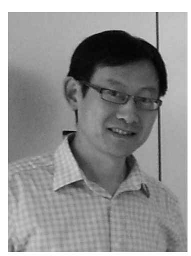
[21] E. Martin, O. Vinyals, G. Friedland, and R. Bajcsy, "Precise indoor localization using smart phones," in *Proceedings of the 18th ACM International Conference on Multimedia*, ser. MM '10. New York, NY, USA: ACM, 2010, pp. 787–790.

[22] J. Shi, L. Meng, A. Striegel, C. Qiao, D. Koutsonikolas, and G. Challen, "A walk on the client side: Monitoring enterprise wifi networks using smartphone channel scans," in *IEEE INFOCOM 2016 - The 35th Annual IEEE International Conference on Computer Communications*, April 2016, pp. 1–9.

[23] K. Yang, S. Ou, and H. H. Chen, "On effective offloading services for resource-constrained mobile devices running heavier mobile internet applications," *IEEE Communications Magazine*, vol. 46, no. 1, pp. 56–63, January 2008.



Xuan Du received the B.Eng. degree in computing and electronics in 2013 from the School of Computer Science & Electronic Engineering, University of Essex, Colchester, U.K., where he is currently pursuing the Ph.D. degree in computing system engineering. His research interests include indoor positioning, the Internet of Things and mobile computing. He involves in the research projects funded by various sources such as UK EPSRC and EU H2020. He is a student member of the IEEE and the IEEE Communications Society (ComSoc).



Kun Yang received his PhD from the Department of Electronic & Electrical Engineering of University College London (UCL), UK, and MSc and BSc from the Computer Science Department of Jilin University, China. He is currently a Chair Professor in the School of Computer Science & Electronic Engineering, University of Essex, leading the Network Convergence Laboratory (NCL), UK. His main research interests include wireless networks, network convergence, future Internet technology and network virtualization, mobile cloud computing and networking. He has published 80+ journal papers and he is a Senior Member of IEEE and a Fellow of IET.

PLACE PHOTO HERE

Dongdai Zhou received the Ph.D. degree in computer science and technology from Jilin University, Changchun, China. He is currently a Professor and Doctoral Tutor with Northeast Normal University, Changchun, China. His research interests include software engineering, digital learning environment theory, method, and key technology.