A Crowdsourcing and Simulation based Approach for Fast and Accurate Wi-Fi Radio Map Construction in Urban Environment

Tatsuya Amano† Shugo Kajita† Hirozumi Yamaguchi† Teruo Higashino† Mineo Takai†*

†Graduate School of Information Science and Technology, Osaka University, Japan

*University of California, Los Angeles

***Abstract*—In order to maintain certain quality of Wi-Fi services even in the congested, uncoordinated ISM bands in urban areas, mobile Wi-Fi clients (i.e. smartphones of pedestrians and vehicle passengers) must be intelligent to carefully choose appropriate access points (APs). For such purpose, Wi-Fi radio map would be of great help to them to make proper AP selections (e.g. vertical handover) along with their movement. However, crowdsourcing-based approaches require a large number of volunteers to monitor and report signals on streets, and war driving is too coarse for accurate map construction in complicated urban building environment. In this paper, we propose a Wi-Fi radio map construction mechanism using both crowdsourcing and highly-precise simulation. Once some cooperative smartphone users collect Wi-Fi beacon data with RSS information, it estimates "tx-tile" for each AP, which is "virtual" transmission source on a wall of the building where AP is inside. Then using this tx-tile with estimated tx-power, it executes online Wi-Fi radio propagation simulations with 3D city models to complement RSS information in many other areas that are not covered by the limited number of cooperative users. We have evaluated the tx-tile localization error and the quality of the radio map. Also we demonstrate our Wi-Fi radio map system for Osaka city.**

I. Introduction

The Japanese government has a national policy of enhancing Wi-Fi availability by the Tokyo Olympic in 2020. This is mainly because Wi-Fi can be a monetary-cost-effective solution for foreign tourists. For the realization of the world's highest level ICT environment, the Ministry of Internal Affairs and Communications issued an action plan, called "SAQ2 JAPAN Project" in June 2014. Likewise, Softbank Group Corp. provided nationwide 400,000 APs (Access Points) for foreigners. The movement toward increasing availability and usability of Wi-Fi in public areas have become more active. In addition, Wi-Fi has also been important as alternative infrastructure of low-cost smart city foundation. For example, in Barcelona, the information from the urban infrastructure like street light illuminance, human flow and noise levels is aggregated through a Wi-Fi-based platform. Wi-Fi is now becoming indispensable infrastructure.

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However, in urban areas, Wi-Fi APs have been deployed densely to increase spatial coverage, which leads to a chaotic and disorderly environment. For such dense Wi-Fi environment, many efforts have been dedicated to increase the performance. For example, the IEEE802.11ax task group reports that Wi-Fi throughput can be nearly doubled using Dynamic Sensitivity Control (DSC) and Transmit Power Control (TPC) [1]. Our research group has been developing the channel selection technique for autonomous and efficient frequency reuse of each AP with the IEEE802.11a/g/n architecture [2]. Besides those researches that consider the throughput improvement of single AP, it is necessary to take the impact of multiple APs into account. For example, interference signals from surrounding APs are likely to incur the performance degradation of clients at the edge of Wi-Fi cells. Careless selection of APs in horizontal handover causes serious quality degradation or disconnection, which finally affects TCP throughput.

As seen, to provide a certain quality even in crowded, unconditioned ISM bands in the city, Wi-Fi clients should intelligently select appropriate APs. Wi-Fi radio map is a promising way of allowing the clients the fast recognition of the surrounding APs and their signal intensity. Recently, the rapid spread of smartphones has made Wi-Fi beacon data sensing much easier [3], [4]. In these approaches, radio information observed by smartphones is stored in a database with geographical coordinates, and the information is used to provide Wi-Fi radio conditions to Wi-Fi clients. However, the naive crowdsensing approaches that simply map the observed signal strength with SSID onto the 2D coordinates have several drawbacks. Most significantly, crowdsensing generally requires a number of cooperative users to cover wide region of urban city, but recruiting them is not easy. Designing and deploying incentive mechanisms is not always successful. Moreover, the signal samples reported by those users may not cover minor streets and spaces often seen everywhere in complicated urban areas. Radio map construction should be supplemented to increase the availability and accuracy.

In this paper, we present a Wi-Fi radio map construction

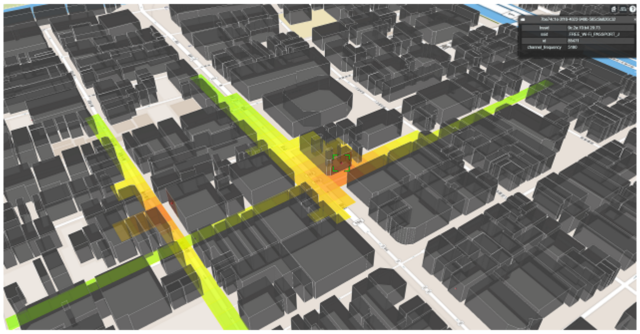


Fig. 1. Wi-Fi Radio Map Visualization (around Yodoyabashi, OsakaCity)

scheme. Similar to several existing approaches, we rely on a crowdsourcing approach where smartphone users help to collect Wi-Fi beacon data. We assume most of APs are inside the buildings in urban environments. To construct Wi-Fi radio map outdoors based on RSS reports from those cooperative users, it is necessary to estimate the exact AP position inside building, which often difficult due to several factors. Therefore, this scheme estimates "tx-tile" for each AP, which is a "virtual" transmission source as if the AP is on the wall of the building in which the AP exists. Then using this virtual location and estimated tx power, it executes online Wi-Fi radio propagation simulations with 3D city models to complement RSS information of uncovered areas. We construct the Wi-Fi radio map from this simulation result.

We evaluated the tx-tile localization error and the quality of the radio map of this scheme in Osaka University campus environment. The localization mean error is 14.65[m] and the simulated RSS samples that the RSS errors were 5[dBm] or smaller were about 65%.

We implemented our crowdsensing and radio map construction scheme and our constructed Wi-Fi radio map of Osaka City by large-scale crowdsourcing data. We are constructing the Wi-Fi radio map of Osaka City as shown in Fig. 1.

II. Related Work

In order to alleviate interference due to the dense deployment, a large amount of effort has been dedicated in different ways. [5] addresses the fact that the transmission power of most Wi-Fi APs is configured to maximum in the factory settings. Therefore, cross-layer control is recommended where the carrier-sense threshold is coordinately controlled with transmission power.

The existing techniques to avoid interference between APs aim to efficiently utilize the space and frequency [5], [6]. They are basically location-independent approaches for resource optimizations. Meanwhile, there are location-dependent (*i.e.*, map-based) approaches that build prior knowledge such as radio database and provide it to APs and clients to assist their decisions and strategy for frequency use. We target such map-based approaches.

One of the significant information for Wi-Fi database is AP location, and there are several methods to estimate it using signal observations. [7] investigates the AP position estimation error that comes from the difference of the Wi-Fi devices used for Wi-Fi scanning. The method proposed in [8] gets radio wave incoming direction using the directional antennas and estimates AP location. [9] and [10] estimate the direction of arrival of radio wave from the change of the receive signal strength with the movement of the observer, and [11] estimates the direction of arrival using a smartphone by rotating the observer at the observation points. [12] uses Channel State Information (CSI) which is information including the phase of Wi-Fi radio waves, which is difficult for ordinary smartphones to obtain. These methods can estimate the location of APs with sufficient accuracy, but they require special devices or special actions to collect the data, which is not suitable for crowdsourcing. Instead, we conduct range-free localization to determine virtual AP location using simple observation samples from smartphones.

Many studies on Wi-Fi handover have been done so far. SyncScan [13] presents handover methods which a separate AP selection and actual handover to minimize the handover delay. [14] and [15] set the common SSID and channel frequency for all APs to eliminate association and authentication process at client side.

There are some methods to survey large scale Wi-Fi radio status by crowdsourcing, war-walking and war-driving [16]. Radio maps generated by these methods are mainly used for smartphone localization in an indoor environments [16]–[18]. Place Lab [16] collects Wi-Fi fingerprints for client localization by war-driving. The difference between scan data by war-driving and war-walking is addressed in [3]. A localization method as well as an indoor and radio map construction indoor is proposed in [17], which estimates the relative positions of APs using multidimensional scaling. Similar to the others, the radio map is used for both Wi-Fi positioning and Wi-Fi network optimization. In [19], smartphones are used for AP spectrum management leveraging their channel scanning capabilities.

Considering the contributions of the prior work, this paper has the following contributions. Firstly, we consider urban Wi-Fi radio map construction with a limited number of cooperative users. In highly-populated urban areas with a lot of minor streets, half-outdoor space where war-driving is not possible, we should rely on war-walking, but coverage becomes a serious issue. We leverage the highly-precise simulations to complement the missing data. Although, there are some techniques to interpolate RSS values based on kriging [20], [21], it is difficult to consider reflection of radio waves by buildings with those methods.

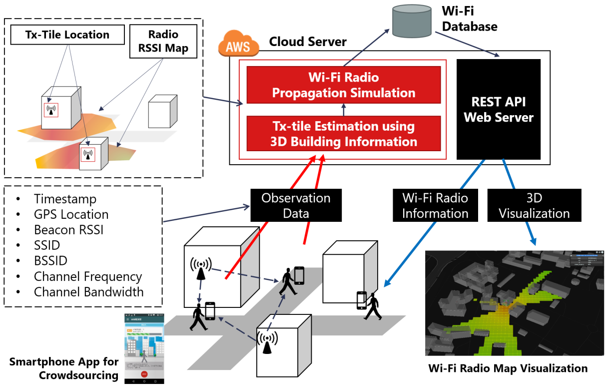


Fig. 2. System Architecture

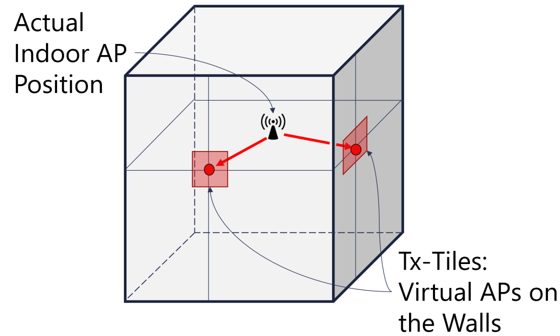


Fig. 3. Tx-tiles for an AP

Secondly, for such purpose, we present a new concept of AP localization in 3D urban model. From the beacon samples from a limited number of smartphones, we estimate virtual tx sources of APs (called tx-tiles) for simulations. Thirdly, we have built the complete system including Wi-Fi sensing android App, Wi-Fi database, online simulation system on 3D map and visualization, which is open to public [22] (http://www.wifibigdata.org).

III. System Overview

Our system architecture is shown in Fig. 2. The system consists of three major components, (i) a *radio map* that is composed of a Wi-Fi database with 3D city street and building models, (ii) a cloud server containing our AP localization, simulation and web API engines, and (iii) cooperative users called *observers* with our smartphone App.

Our radio map contains Received Signal Strength (RSS) values from APs at any points of outdoor spaces such as major and minor streets, public spaces and parks in urban areas. Using this map, Wi-Fi clients, Wi-Fi APs and Wi-Fi service providers can know how strongly the desired/undesired signals reach from the surrounding APs. This information can be used for multiple purposes such as autonomous AP selections by clients, autonomous channel selection by APs and channel optimization by service providers. We note that there are two types of RSS values, *monitored* and *simulated*. The monitored RSS values are those actually observed by the observers' smartphones while the simulated RSS values are the estimated values by our online radio propagation simulations. Both types of values are on the same radio map to accomplish a sort of data assimilation. The radio map also contains the virtual positions of APs called *tx-tiles*. These are calculated by our simple range-free 3D localization algorithm using the data sent by the observers' smartphones. The observers are required to install our smartphone app and run it background to sense ESSIDs (SSID texts), BSSIDs (MAC addresses), RSS, channels and bandwidth (20MHz/40MHz etc.) by beacon advertisement from APs. They just walk with their phones in hands and our app detects and estimates the observers' walking behavior to report those information with GPS locations, with appropriate timing and intervals.

Using the data by observers, our localization algorithm engine estimates "tx-tile" for each AP by range-free localization with 3D city models. A tx-tile is a "virtual" transmission source on the wall of the building where the AP is inside (Fig. 3). Considering the fact that most APs that are observable from streets are inside buildings in urban environments and radio propagation is affected by many things like walls, rooms, windows and their materials, it is not a good approach to exactly estimate the physical AP locations. Accordingly, we estimate the information which is necessary for our simulation, and we believe the tx-tile localization is a reasonable solution. Besides, we adopt a range-free localization method because the measured RSS values by smartphones fluctuate due to attitude of smartphones or other environmental factors such as humans, trees and moving vehicles.

Then using tx-tile information, the system executes online Wi-Fi radio propagation simulations with 3D city models to complement RSS information in many other areas that are not covered by the observers. Finally, for each observed AP, all the information about ESSID, BSSID, the estimated location and transmission power of the tx-tile, RSS values at each location, channel frequency and bandwidth are aggregated in the Wi-Fi database.

The Wi-Fi AP information in the database can be accessed by Wi-Fi clients via the REST API server and the clients can get APs information by providing their locations. The radio map is visualized on the 3D city map through Web browsers. Such visualization is helpful for AP placement and deployment that needs AP density and channel frequency occupancy information.

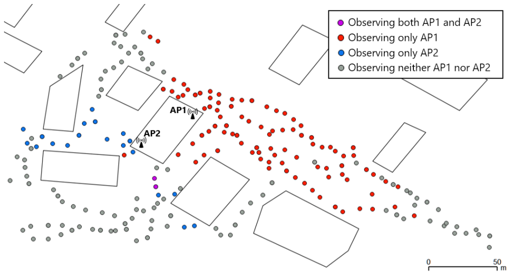


Fig. 4. AP Locations and Observation Points in Preliminary Survey

TABLE I
PRELIMINARY SURVEY

Setting	
Wi-Fi AP Model	Buffalo AirStation WHR-300HP
AP Protocol	802.11g
AP Channel Bandwidth	20MHz
Observation Client	LG Nexus 5X
Number of Observation Point	258

IV. CONSTRUCTION OF WI-FI RADIO MAP

In this section, assuming that we obtain the observation data from the observers, we explain how to localize tx-tiles and how to determine their transmission power. It is done in the following three steps; (i) estimate tx-tile candidates using the observation data for each AP, (ii) estimate the location of each tx-tile by fitting the simulated RSS values to the observed RSS values, and (iii) determine the transmission power of tx-tiles for final calibration.

We let o denote each point of reception (PoR) of an AP's beacons and O denote a set of such points. Similarly, each non-PoR is denoted as $\overline{o}$ and $\overline{O}$ is a set of such points. A non-PoR is an observation point where no beacon from a target AP is observed.

A. Step 1: tx-tile candidates estimation

Basically, tx-tile candidates are determined by range-free localization with multiple observation points. We consider the maximum range of beacon transmission from an AP, and consider the sphere centered at a PoR with the maximum transmission range. Ideally, each tx-tile should be contained in this sphere, but the observations of RSS values by smartphones are not always accurate due to their antenna design limitations. Therefore, we adopt majority-voting by multiple observations where the tile on each wall of a building which is contained by the largest number of spheres is regarded as tx-tile.

To justify our strategy, we conducted a preliminary survey to design the maximum transmission range mentioned above to determine the sphere diameter. The survey setting is shown in Fig. 4 and Table. I. We installed two APs (AP1 and AP2) and measured RSS of beacons received from the two APs at 258 points. Consequently, beacons from AP1 were observed at 115 points and those from AP2 were at 27 points. Fig. 5(a) shows the observed RSS values and the distance between the PoR and the APs.

Then we consider the maximum transmission range based on the free-space propagation model. The model calculates RSS in free space without obstacles between the transmitter and the receiver. In Eq. (1), P_r is the received power [mW], L is the free space path loss, P_t is the transmission power [mW], G_t is transmission gain and G_r is reception gain.

$$P_r[W] = \frac{P_t G_t G_r}{L} \tag{1}$$

Free space path loss is calculated in (2) where d[m] is distance between the PoR and the AP and λ is wave length.

$$L = \left(\frac{4\pi d}{\lambda}\right)^2 \tag{2}$$

Then, the distance from PoR to the APs can be estimated by RSS in (3), where P_0 is transmission power of the AP.

$$d = \frac{\lambda}{4\pi}\sqrt{\frac{P_0}{P_r}} \tag{3}$$

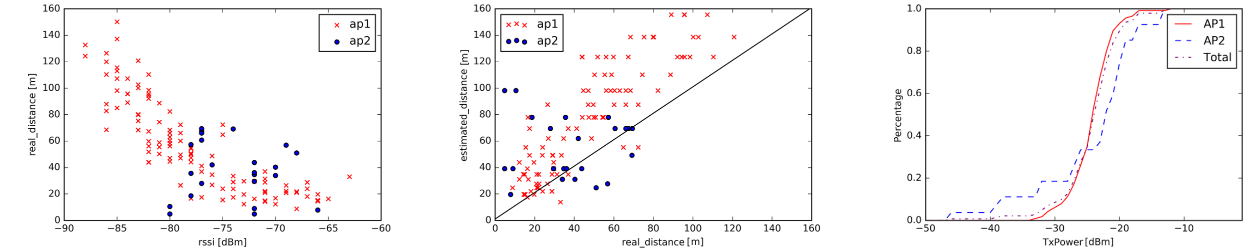
In the urban environment, the actual path loss is likely to be larger than the free space path loss due to a variety of noises and obstacles. Therefore, it is considered that the distance calculated by the free-space model is longer than the actual distance to the AP and accordingly, we adopt the distance calculated from the free-space model as the sphere diameter.

The remaining issue is how to estimate the transmission power P_0. Fig. 5(c) shows the percentage that the APs are actually included in the spheres, changing the transmission power of APs from -50[dBm] to -10[dBm] in the above experiment. If the transmission power is -20[dBm], about 90% of spheres include APs. Hence we empirically set -20[dBm] as the transmission power of APs. Fig. 5(b) shows the actual distance and estimated distance to the APs assuming -20[dBm] as the transmission power.

In summary, for each PoR o where beacons from an AP are observed with o_v[mW], we calculate the sphere $s(o)$ centered at the PoR with radius r calculated in Eq. (4). The wave length λ is $\frac{300\times10^6}{24000\times10^6} = 0.125$[m] if the AP uses 2.4GHz band, and λ is $\frac{300\times10^6}{5000\times10^6} = 0.06$[m] in case of 5GHz band.

$$r = \frac{\lambda}{4\pi}\sqrt{\frac{0.001}{o_v}} \tag{4}$$

In addition, in order to fully utilize observations, we consider another type of sphere where a target AP is not included (we call it *negative sphere*). Negative spheres can be obtained based on the fact that a beacon is not observed



(a) RSS vs Actual Distance to APs from Observation Points (b) Actual Distance vs Estimated Distance to APs (c) Percentage of Spheres that include APs

Fig. 5. RSS Observation Results

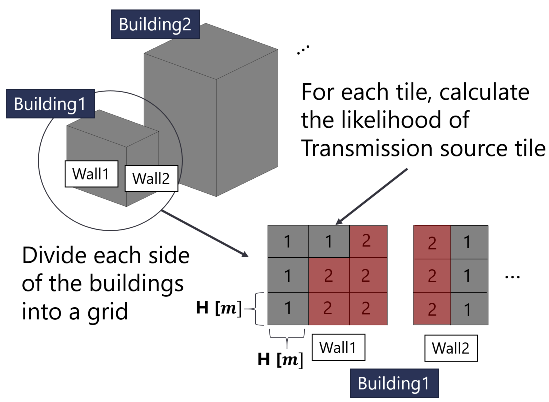


Fig. 6. Tiles of Buildings

at a certain point. If we do not observe any beacon from an AP just beside a building wall, the probability that the AP is near the observation point on that side of building is low. According to this, for each non-PoR $\overline{o}$ where no beacon from a target AP is observed, the negative sphere $\overline{s}(\overline{o})$ is defined as that centered at the point with radius r, which is empirically defined as 10[m]. Compared with the positive sphere defined earlier, the number of negative spheres tends to be large since beacons are not observed at such observation points that are apart from the AP. So we may limit the non-PoRs that create negative spheres to those within 200[m] from the centroid of the observation points of the AP.

Next, we will explain a method for estimating tx-tile candidates based on the set $\{s(o)|o \in O\}$ of positive spheres and the set $\{\overline{s}(\overline{o})|\overline{o} \in \overline{O}\}$ of negative spheres. Firstly, we divide each wall of building into square tiles like Fig. 6, and for each tile t in the grid, we calculate the likelihood $\mathcal{L}(t)$ that the AP's tx-tile exists on the tile. The likelihood $\mathcal{L}(t)$ is calculated in (5). We set the tile size to 5[m]×5[m].

$\mathcal{L}(t)$

TABLE II
SIMULATION PARAMETERS

Parameters	Values
Simulator	Scenargie
Propagation Module	Fast Urban Propagation Module
Pathloss Calculation Model	VPUP
AP's Phy Protocol	802.11g or 802.11ac
Transmission Power	-10 [dBm]
Max Signal Propagation	100,000 [km]

$$= \sum_{o \in O} f(o_v) \cdot intersects(c, o) - \sum_{\overline{o} \in \overline{O}} intersects(c, \overline{o}) \tag{5}$$

where

$$intersects(t, o) = \begin{cases} 1 & \text{(if } t \text{ is within } o) \\ 0 & \text{(otherwise)} \end{cases}$$

$$f(o_v) = \begin{cases} 9.2 & (o_v \geq -75) \\ 3.5 & (-75 > o_v \geq -83) \\ 1.6 & (o_v < -83) \end{cases}$$

$f(o_v)$ in (5) is a weight function. We give more weights to the PoRs with larger RSS values, *i.e.*, positive spheres with smaller radius. So we classify the positive spheres according to the RSS values into three levels. The PoR with -75[dBm] or larger are in Level1, those with values between -75[dBm] and -85[dBm] are in Level2, and those with -85[dBm] or smaller are in Level3. We note that we refer to [17] to determine the thresholds. The weight for each level is calculated based on the real observation data in Osaka City. Based on the 1,906,339 observations in Osaka City, the number of observations classified into Level1, Level2 and Level3 is 207,668, 531,598 and 1,167,073, respectively. We use each ratio of the observations as the weight for the level, and we choose the tiles with the highest likelihood as the tx-tile candidates.

B. Step 2: tx-tile location estimation

In the second step, we select one tx-tile for each wall from the tx-tile candidates in the first step. For this purpose, we execute several simulations using different tx-tiles and

Fig. 7. Radio Propagation Simulation

select the best one that gives the best-fit simulation to the actual observations.

Simulation settings are shown in Table II. We use the Scenargie simulator and the Fast Urban Propagation module. In the simulation scenarios, we place APs at the center of the tx-tile and obtain the simulated RSS values in surrounding area as shown in Fig. 7.

The detailed algorithm to find the best-fit tx-tile is shown in Algorithm 1 where $B = \{b\}$ is a set of buildings within 500[m] from the center of the observation points and b_H is the number of vertical tiles in building b. For example, when the size of each tile is 5×5 and the height of b is 30, b_H is 6. T is the set of tx-tile candidates and $T_{b,w,h} \in T$ is the set of h-th tx-tile candidates from the bottom, which are on the wall w of building b. $Simulation$ is a function that takes $tiles$ as inputs and returns $RadioMap$ generated by a radio propagation simulation with APs installed at the center of each tx-tile in $tiles$. $RadioMap$ is also a function that takes a point as input and returns simulated RSS values at the point. $Error$ is defined in (6). If the tx-tile candidates exist on more than one wall of the building, we select one tile from each wall, and execute simulations with all the combinations of the selection. We consider the tiles that output the radio map with the least error as the tx-tiles of the AP.

$$Error(RadioMap, O) = \frac{1}{|O|} \sum_{o \in O} |RadioMap(o) - o_v| \tag{6}$$

C. Step 3: Transmission Power Estimation

In the 3rd phase, we estimate the transmission power of the tx-tile. As in the second step, we execute several simulations with different transmission power using the tx-tile estimated in the second step. Transmission power is selected from -20, -10, 0 and 10 [dBm]. Using (6), we calculate the error of radio maps generated by simulation for each transmission power and select the radio map with the least error. Then we adopt this map as the Wi-Fi radio map of the AP.

Algorithm 1 Txtile Selection by Simulation Fitting

Input: B, O, T
Output: $txtiles$
  for b in B **do**
    $txtiles \leftarrow \{\}$
    $min\_error \leftarrow \infty$
    $h \leftarrow 0$
    while $h < b_H$ **do**
      $h \leftarrow h + 1$
      $tile\_combinations \leftarrow \sqcap_w T_{b,w,h}$
      for $tiles$ in $tile\_combinations$ **do**
        $RadioMap \leftarrow Simulation(tiles)$
        $error \leftarrow Error(RadioMap, O)$
        if $error < minerror$ **then**
          $txtiles \leftarrow tiles$
          $min\_error \leftarrow error$
        end if
      end for
    end while
  end for

TABLE III
EXPERIMENT ENVIRONMENT

Parameters	
Wi-Fi AP1-AP4 Model	Buffalo AirStation WHR-300HP
Wi-Fi AP5 Model	Buffalo AirStation WZR-600DHP
Wi-Fi AP6 Model	Buffalo NFINITI WZR-AMPG300NH
AP Protocol	802.11g
AP Channel Bandwidth	20MHz
Observation Client	LG Nexus 5X
Number of Observation Point	246

V. Experiment

To evaluate the tx-tile localization error and the quality of a radio map constructed by the proposed scheme, we experimented in Osaka University campus environment. We installed 6 APs (AP1 to AP6) near the windows of department buildings. APs' positions and observation points are shown in Fig. 8. Some other settings are shown in Table. III. We could not observe the beacon of AP4 at any points.

We evaluated the tx-tile localization error. We estimated the tx-tile based on the proposed scheme. Figure. 14 shows the actual AP locations and estimated tx-tile locations. Tx-tile localization errors are shown in Table. IV. AP2 has two tx-tiles as AP2's tx-tile candidates exist on multiple walls. The average error is 14.65[m]. For each AP except AP6, the building which the estimated tx-tile is in matched with the building the AP is in.

A. Quality of Radio Map RSS

We constructed the radio map using 246 of the 296 observation points and using the left 50 points, we compared actual RSS and estimated RSS on the radio map

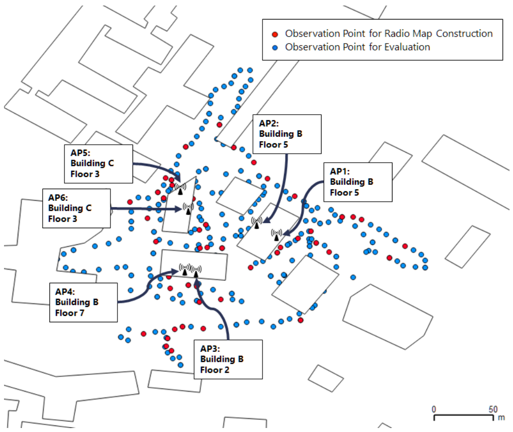


Fig. 8. AP Location and Observation Points

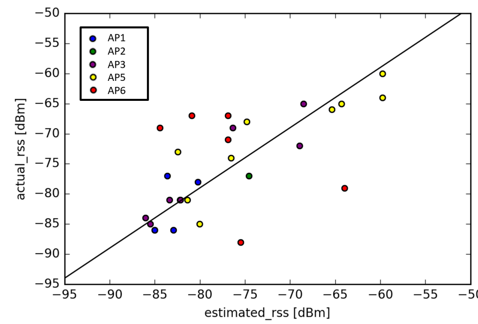


Fig. 9. RSS Estimation Error

TABLE IV
TX-TILE LOCALIZATION ERROR

Tx-tile	Error[m]
AP1	18.7
AP2 tx-txtile-1	10.1
AP2 tx-txtile-2	17.4
AP3	2.7
AP5	12.3
AP6	26.7

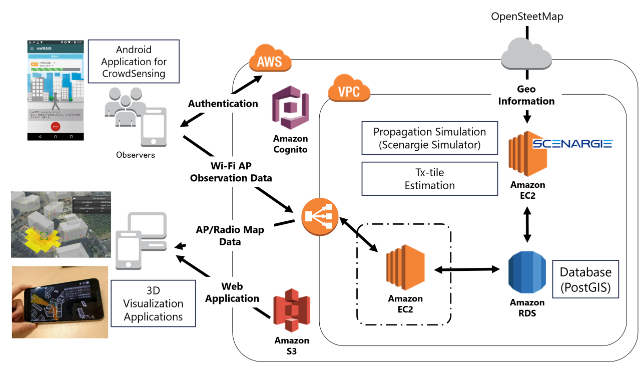


Fig. 10. System Implementation with Amazon Web Service

for the 6 APs installed. Fig. 9 shows the actual RSS and estimated RSS in the constructed radio map at the evaluation points. Among the 50 points, the number of points that observed AP1...AP6 was 5, 1, 8, 0, 9 and 6, respectively, therefore and the number of observation is 29. At 19 of the 29 observations, the error remained within ±5[dBm]. The error of RSS of the AP5 is relatively large. This is because AP5 has a large tx-tile localization error. Hence, we can assume that the tx-tile localization error has a great influence on the accuracy of the radio map.

VI. BEST CHANNEL SELECTION USING WI-FI RADIO MAP OF OSAKA CITY

We have built the system of large-scale crowdsensing and radio map construction. Also, using this system, we have constructed a radio map of Osaka City [22]. The architecture of the entire system is shown in Fig. 10. We have constructed the system including Wi-Fi sensing android App and 3D visualization application with Amazon Web Service. We use 3D city models of OpenStreetMap for tx-tile localization and propagation simulation.

We collected observation data in Osaka City using our system. The target area of observation is about 5[km^2]. Fig. 12 shows the area where observation data have been collected. The observers holding the smartphones (Nexus 5) in their hands walked to cover almost all the roads in this area. We got observations covering all areas on three different days.

The number of total observation points is 42,022, and the number of observed APs is 78,170. From those observation data of the 1st day and the 2nd day, we construct the radio map using the simplified proposed method. In the simplified method, to reduce the simulation patterns, the size of tiles is 10[m]×10[m]. Moreover, the transmission power estimation in the 3rd step is skipped and the transmission power of each tx-tile is fixed to -10[dBm]. By excluding common APs that appeared on all day observations, mobile AP can be excluded from the targets. We evaluated the quality of the map comparing RSS information in constructed radio map and the actual RSS of 3rd day observation. Fig. 11 shows the evaluation in Yodoyabashi of Osaka city, where the number of observations is 870, and the number of target APs is 343.

This map would be a great help for mobile Wi-Fi clients to know the best channel at an arbitrary point. In [2], our research group has proposed a prediction function to select the best channel for channel migration based on IEEE 802.11 MAC frame monitoring, large simulation dataset, and machine learning techniques. By using the radio map, mobile clients can know RSS information of any points without sensing and can estimate channel delay with the RSS information and the prediction function.

Using the assumed traffic of each channel used in [2],

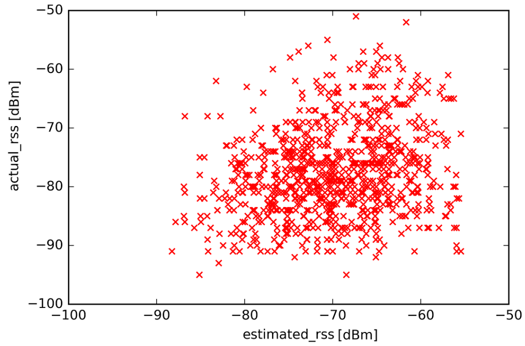


Fig. 11. Yodoyabashi Evaluation: RSS comparison

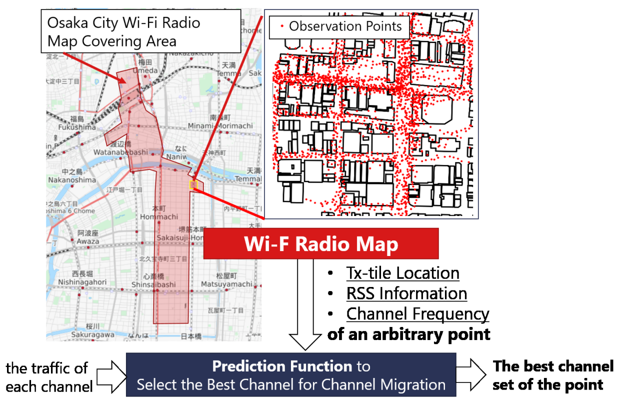


Fig. 12. Osaka City Wi-Fi Database Usage

and RSS information in the Osaka city radio map, we confirmed, in a simulation, that we can estimate the best channel set from our function at a point. Fig. 13(a) shows the target point and the simulation environment and Fig. 13(b) shows the comparison of the function output and ground truth from simulation at the point. In this way, it is possible to estimate the channel situation of any point using the Wi-Fi radio map at the point. The map is also helpful for those who want to install a new AP in urban areas to know channel state at an arbitrary point. Moreover, combining the radio map and the prediction function, 3D visualization application of the radio map become more useful for considering a channel and position of a new AP.

VII. Conclusion

A. Tx-tile Localization Error

In this paper, we have considered urban Wi-Fi radio map construction with a limited number of cooperative users and presented a new concept of AP localization in 3D urban model. From the beacon samples from a limited number of smartphones, we estimate virtual tx sources of APs (called tx-tiles) for simulations. We have built the complete system including Wi-Fi sensing android App, Wi-Fi database, online simulation system on 3D map and visualization, which is open to public [22]. We evaluated the tx-tile localization error and the quality of the radio map of this scheme in Osaka University campus environment, and mean localization error is 14.65[m] and the observations with 5[dBm] or smaller errors were about 65%. We have built the crowdsensing and radio map construction system and constructed the Wi-Fi radio map of Osaka city by large-scale crowdsourcing data. In future, it will be necessary to conduct more detailed experiments on tx-tile localization and improve the accuracy of tx-tile location estimation of tiles by using highly accurate information such as public Wi-Fi spot location information which is published on the Web or observation data from indoor.

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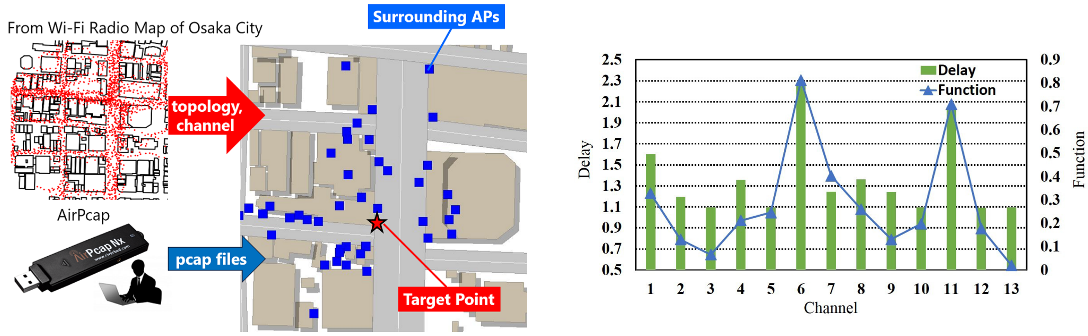
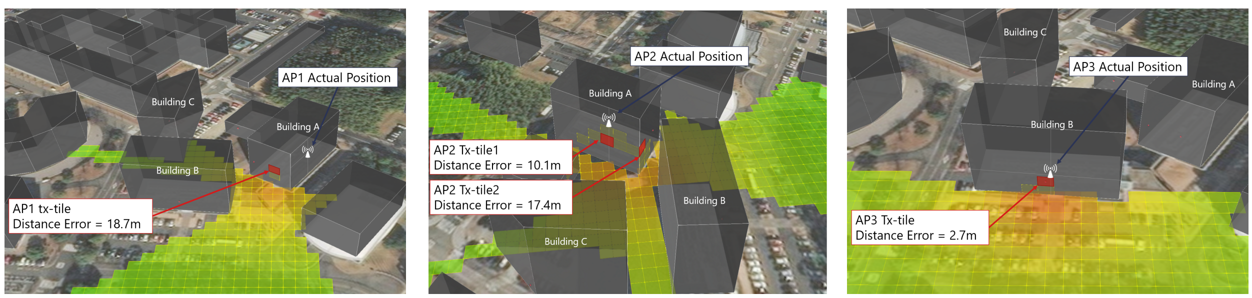


(a) Application Example: The Best Channel Selection

(b) Relative Prediction Result

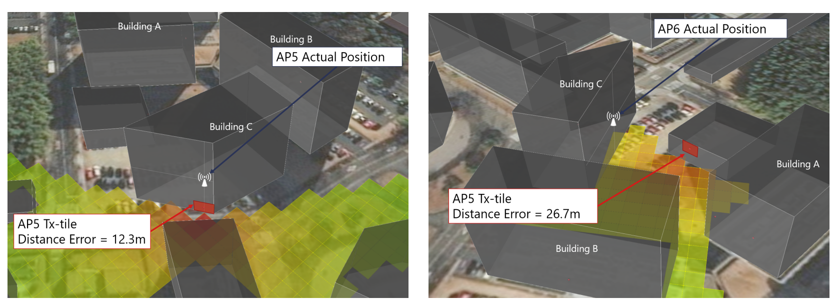
Fig. 13. Best Channel Selection with Osaka City Radio map



(a) AP1

(b) AP2

(c) AP3



(d) AP5

(e) AP6

Fig. 14. Estimated Tx-tile Location

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