Human Indoor Positioning via Passive Spectrum Monitoring

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***Abstract*—With the advancement of navigation technologies, indoor localization has become an essential function in our daily life. However, the existing methods of human indoor positioning are mainly based on active sensing or labeling techniques, so the application of indoor localization is restricted by utilizing these current approaches. For example, when the location of the signal transmitter is unknown, or the target does not carry a tag, it is challenging to recognize the position of the target. Therefore, it is important to design a suitable approach to achieve indoor positioning. This paper proposes a new approach, which uses passive radio frequency signals to accurately locate the human subject indoor. Since human occupancy can alter the passive spectrum, and human at different locations can generate different signatures on the spectrum, these spectrum characteristics can be utilized to achieve human positioning. Cognitive radio is applied to collect passive radio frequency (RF) signals in the frequency bands that are sensitive to human occupancy. Two machine learning algorithms are used to achieve indoor positioning. A decision tree is used to classify a human subject's position on a grid. The result of classification can verify that human occupying different indoor locations can generate different RF signatures on the passive spectrum. Then Gaussian process regression is employed to estimate the coordinates of the human subject. This process provides a higher resolution of indoor localization than the decision tree algorithm. The experiments show a positioning error as low as 0.8m among all tested scenarios.**

Keywords—indoor positioning, passive radio frequency, spectrum monitoring, human RF signatures

I. Introduction

The development of mobile computing devices and the advancement of wireless network technology have made positioning technology a hot research topic. Positioning technology has been applied in different areas ranging from national defense to security in our daily lives. For instance, military navigation services such as intelligence collection, explosion monitoring, and emergency communications all depend on accurate positioning of human operators. Applications such as private navigation, monitoring, rescue, and transportation are in a huge demand. Therefore, positioning technologies have become an essential function in our life.

The Global Positioning System (GPS) is a mature positioning system based on satellite signals. However, it is not suitable for indoor positioning. First, the materials of the building can appreciably attenuate the satellite signals. Second, there are many electronic devices in indoor environments. The presence of these signals interferes with the transmission of satellite signals. This will greatly lower the accuracy of GPS based positioning in an indoor environment. Therefore, positioning technologies other than GPS are required for indoor positioning.

Indoor positioning methods are mainly based on tags and active signals. Users need to obtain information about the signal source, or add tags to the target, and acquire data from the tags to achieve the target's position. These methods have some limitations. For example, when the location of the signal transmitter is unknown, or the target does not carry a tag, positioning becomes very difficult. In this paper, we propose a method that is based on the passive RF spectrum, which requires neither knowing the origin of signal source nor tagging the human target to achieve indoor positioning.

Human's occupations at different indoor locations can generate different RF signatures on the passive spectrum. Our method estimates human locations by detecting and processing the variations of the scanned spectrum. The contributions of this paper are as follows. First, we developed a novel positioning technique based on subtle alterations of the passive spectrum to detect human occupancy of different locations. Second, we verified using a decision tree to roughly estimate the person's position on a grid. Third, we employed the Gaussian process regression (GPR) method to accurate the indoor localization result, which enriched the practical positioning methods in the field. Forth, only low-cost devices were used to acquire RF signals in our research, and the average error is lower than 0.8 m, which have proved the practicability and affordability of the proposed approach.

The remaining sections of this paper are organized as follows. Section II introduces the existing positioning techniques in the field, and describes the advantages of our technique. Section III presents the proposed technique and the

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experimental design. Section IV shows the experimental results. Section V discusses the conclusion and future direction of our research.

II. Related Works

A. Existing Technologies

The current positioning technologies include infrared positioning, ultrasonic positioning, WIFI positioning, and radio frequency identification (RFID) positioning. These methods currently used in indoor positioning are discussed below.

Infrared positioning is used to locate targets by receiving the modulated infrared signal sent by optical sensors installed indoors [1]. This technology has high indoor positioning accuracy. Since light cannot penetrate obstacles, infrared rays can only travel within the line of sight and are easily interfered by other light [2]. The localization performance by using infrared positioning technique cannot perform well when objects exist on the site. Besides, to efficiently receive infrared, amount of antennas must be installed on experimental site, which leads to higher costs.

Ultrasonic positioning are widely used for positioning, and the reflection measurement value is used to calculate the distance to the reference node based on the time difference between the transmitted ultrasonic wave and the response echo of the reference node [3]. Authors of [4] who introduced Active Bat are the pioneers of the ultrasonic positioning system. Intensive deployment of a large number of ultrasonic receiving devices is required to achieve a positioning accuracy with a minimum error of 3cm. Although ultrasonic positioning technique can be used in a non-line of sight circumstance with high positioning accuracy and small errors, the cost of the devices is high. Moreover, the transmission attenuation of ultrasonic signals cannot be avoided, so the effective positioning range of this technique is somehow limited.

WIFI positioning as a Wireless Local Area Network (WLAN) is composed of wireless routers, and wireless access points, which can realize positioning, monitoring, and tracking tasks in complex environments [5]. Signal propagation models can be used to locate the receiving mobile device. The highest accuracy is between 1 m and 2 m [6]. However, the disadvantage of WIFI positioning is that this technique highly depends on wireless routers and access points, and these WIFI devices must stay online while working. Therefore, this method has certain limitations.

RFID positioning uses radio frequency signals and signal strength to detect positions. In [7], an aggregation algorithm is developed to locate targets in three-dimensional space. The hardware tags in the system are distributed in a network without a signal source, and the distance between tags is characterized by the strength of the signals detected by the tags. This method heavily depends on the tags on the target, which limits the application of this technique.

B. Discussion

Comparing with the above mentioned indoor positioning methods, there are some differences with our method. First, the signals utilized in our method are passive RF signals instead of active signals. This is an efficient and environmental friendly method because a new signal source is not needed in a space. Nowadays, our environment is already crowded with various RF signals, which leads to a lot of electromagnetic pollution. Radiation of RF signals can be harmful to people's health. Therefore, passive sensing techniques are preferred over active sensing techniques if they can achieve the same level accuracies.

Second, our method does not require human subject to carry any tags or receiving devices. This is completely different from the traditional approaches which build a radio map based on received radio signal strength to realize positioning. Our method deploys software defined radio (SDR) at multiple fixed locations and scans the passive spectrum at those locations. Machine learning methods are applied to map spectrum alterations to human locations. This eliminates the need of tagging the targets or carrying a device, which is beneficial in the applications of monitoring.

Third, Gaussian process regression (GPR) is a non-parametric model that uses Gaussian process priors to perform regression analysis on data. GPR can provide the posterior of the prediction result, and when the likelihood is normally distributed, the posterior has an analytical form. GPR has been applied in the fields of image processing and automatic control [8]. GPR is very suitable for solving positioning problems [9]. The prediction results obtained by GPR are highly accurate [10]. The advantages of GPR include using only a few training data points for regression to acquire all position results, predicting high-dimensional data, and flexibly using different kernel functions to construct the relationship between the independent variables and the dependent variables [11]. In our work, the independent variables are passive RF spectrums, and the dependent variables are human occupying positions. We used the GPR model to infer the relationship between the passive RF spectrums and human occupying positions.

Last, RTL-SDR, a software defined radio, is used to collect passive RF signals in our method. SDR has been widely used in communications and spectrum monitoring, specifically in improving the power amplifier system and transmitter architecture [12], and receiving nerve signals in animals [13]. We have tuned the SDR to scan only the frequency bands that are sensitive to human occupancy to improve power efficiency [14]. Moreover, the devices used in our experiments are low cost, compact, and easy to deploy.

III. Methodologies

Our recent research shows the presence of human subjects can be detected via passive RF signals [15]. The experimental results suggest that human can cause variations in the passive spectrum. In this work, we find that human subject at different locations can generate different signatures on the passive spectrum. Utilizing machine learning algorithms to associate these spectrum characteristics with the corresponding human occupancy locations can help achieve indoor positioning.

The proposed human positioning method includes 3 steps: data acquisition, data pre-processing, and classification and estimation of human subject position by decision tree and Gaussian process regression. In the first step, 6 SDRs were deployed to collect data at multiple locations simultaneously in an indoor environment. In the second step, the pre-process was to calculate the signal power from collected raw data. In the third step, two machine learning algorithms were used for the classification and estimation of human position. A decision tree was used to classify the signal power spectrums of human occupying different positions. This process can verify that human at different locations can generate different signatures on the passive spectrum. Last, GPR was used to build a model between the signal's spectrums and the location coordinates of the human subject. According to the GPR model and signals spectrums of unknown positions, the positions of the human subject can be estimated. The details about data acquisition, data pre-processing, and classification and estimation of human subject position are described in the following subsections.

A. Data Acquisition

RTL-SDR was used to collect RF signals data in our experiments. The SDRs can scan the spectrum frequency from 24MHz to 1760MHz. Our previous research shows that the frequency band around 330MHz is the most sensitive to human occupancy. In this work, frequency bands range from 300MHz to 420MHz were scanned. The sampling rate is 2.4MHz. The experimental site was a classroom at Oakland University. The size of the classroom was 10m×12m. Six devices of the same model are placed around the classroom. Their locations are shown in Fig. 1 as green dots. Then, 20 locations evenly distributed in the classroom were selected for human occupancy. The distance between neighboring points was 1.8m. A human subject occupies one location when six SDRs scan the spectrum simultaneously. Only one human subject was inside the classroom during the experiments. The distributions of the devices and points are shown in Fig. 1.

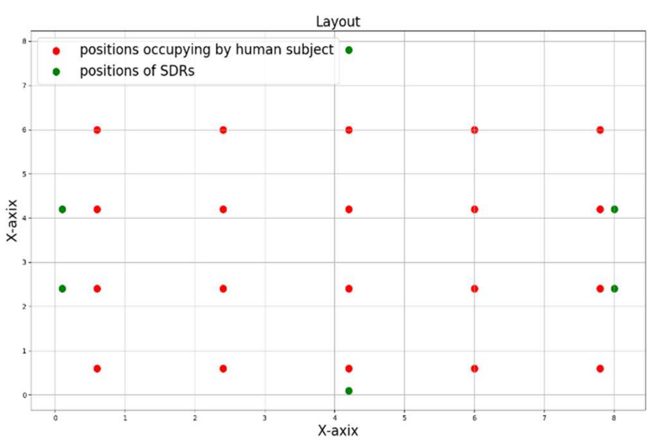

Fig. 1. The Distributions of the Devices and Human Occupying Locations.

The 20 locations are numbered sequentially from the upper left to lower right one row after another. For example, the points in the first row are numbered 1 to 5 from left to right, and so on. The data collected with different human occupancy locations are used differently in the decision tree and GPR algorithms, which will be discussed later in details. The coordinates of each occupancy location are recorded to facilitate the training of GPR.

B. Data Pre-processing

In our experiment, the input of the decision tree and GPR is the power spectrum density. The average power of each frequency band is calculated as follows:

$$P(f) = 10 \cdot \frac{\log_{10} \sum_{i=1}^{N} \left(\frac{s_i}{127.5} - 1\right)^2}{\frac{N}{2}} \tag{1}$$

where P is the average signal power of the frequency band centered at f. N is the number of samples per frequency band. s_i is the value of raw data of the i-th received by each device. The frequency band ranges from 300MHz to 420MHz. A total of 100 frequency bands are scanned. The power spectrum density collected by the 6 SDRs is shown in Fig. 2.

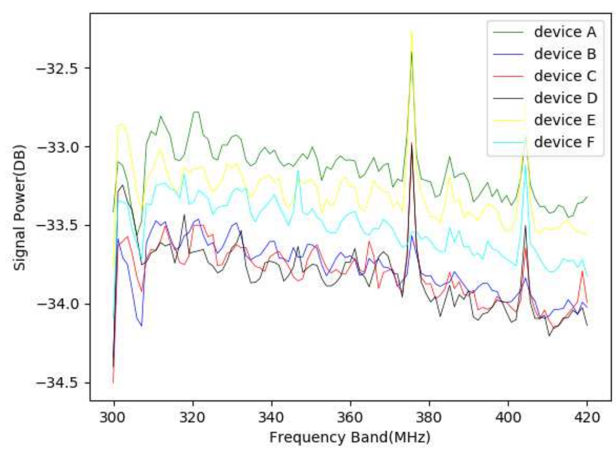

Fig. 2. The Power Spectrum Density Collected by the 6 SDRs When Location 1 is Occupied by a Human Subject.

C. Decision Tree

The decision tree is a classical machine learning approach. Each internal node in the decision tree model represents the judgment of the attribute, each branch represents the output of a judgment result, and each leaf node represents a classification result [16]. A decision tree can classify data sets layer by layer according to feature values. The advantage of the decision tree is that the computational complexity is not high, and the classified results can be presented intuitively.

In this study, it is very important to verify whether a human subject at different locations can generate different RF signatures on the spectrum. A decision tree method is applied to test the hypothesis. If the spectrums obtained when different positions were occupied by human subject can be classified by decision tree with high accuracy, it will be a strong evidence that the hypothesis is true. There are 20 positions tested in our experiments. The signal spectrums obtained at each human occupying position is used as the input of the decision tree. The output of the decision tree is the index of the position.

D. Gaussian Process Regression

The process of using GPR to solve the problem is introduced as follows. The first step is to choose the appropriate mean function and kernel function. The kernel function in GPR is the covariance function. The second step is to calculate the kernel matrix of the training samples. The third step is to calculate the kernel vectors of the points to be predicted and all points of the training samples. Finally, the prediction values are obtained through the function of means and covariances. The GPR method is applied in our research as follows.

First, the training set D for GPR is as follows:

$$D = (x, y) = \{(x_i, y_i)\}_{i=1,\ldots N} \quad (2)$$

where the N-dimensional inputs vector x represents the stacked spectrum of multi-sensors collected by SDRs when the i-th position is occupied by human subjects. The output y_i is the coordinates of the location occupied by the human subject. GPR only depends on the mean $m(x_i)$ and covariance $k(x_i, y_i)_{i,j=1,\ldots N}$.

$$m(x_i) = E[f(x_i)] \quad (3)$$

$$k(x_i, y_i)_{i,j=1,\ldots N} = E\left[\left(f(x_i) - m(x_i)\right)\left(f(x_j) - m(x_j)\right)\right] \quad (4)$$

The GPR model is to infer the relationship $f: x \to y$, which maps a spectrum x to a position y. The conditional distribution of y is determined when the x is given. The function of as follows:

$$f(x_i) \sim GP\left(m(x_i), k\left(x_i, x_j\right)\right) \quad (4)$$

$$y = f(x) + w \quad (5)$$

where $w \sim N(0, \sigma_i^2)$ is the measurement noise. $m(x_i)$ is the mean. $k(x_i, y_i)_{i,j=1,\ldots N}$ is the covariance. Usually, when the data is preprocessed, the mean value is 0. Then the prior distribution of y can be expressed as follows:

$$y \sim N(0, K(x, x) + \sigma_i^2) \quad (6)$$

In function (6), $K(x, x) = K_N = \{k(x_i, x_j)\}_{i,j=1,\ldots N}$ is a $N \times N$ covariance matrix. The joint distribution of training set (x, y) and test set (x_*, y_*) can be expressed as follows

$$\begin{bmatrix} y \\ y_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(x, x) + \sigma_N^2 I_N & K(x, x_*) \\ K(x_*, x) & k(x_*, x_*) \end{bmatrix}\right) \quad (4)$$

where $K(x, x_*) = K(x_*, x)^T$ is a $N \times 1$ covariance matrix between the test set x_* and the input x of the training set. $k(x_*, x_*)$ is the covariance matrix of test point x_*. I_N is the N-dimensional identity matrix. In our work, the squared exponential covariance is chosen to be the kernel function. The function of the kernel is presented as follows:

$$k\left(x_i, x_j\right) = \sigma^2 \exp\left(-\frac{d\left(x_i, x_j\right)^2}{2l^2}\right) \quad (5)$$

In this function, σ is constant. $d(x_i, x_j)^2$ represents the Euclidean distance. l is the length scale of the kernel function. For fear that the trained model is overfitting or underfitting, the value of σ needs to be determined carefully. l needs to be given an initial value and boundary. Then the posterior distribution of $f(x_*)$ can be calculated using the functions below:

$$P(f(x_*)|x_*) = N(\mu_*(x_*), \sigma_*^2(x_*)) \quad (6)$$

$$\mu_*(x_*) = K(x_*, x)[K(x, x) + \sigma_N^2 I_N] f(x) \quad (7)$$

$$\sigma_*^2(x_*) = k(x_*, x_*) - K(x_*, x)K(x, x) + \sigma_N^2 I_N^{-1} K(x, x_*) \quad (8)$$

$P(f(x_*)|x_*)$ is the conditional probability of $f(x_*)$. $\mu_*(x_*)$ is the mean of prediction corresponding to x_*, which is the coordinate of position $f(x_*)$. $\sigma_*^2(x_*)$ is the variance of the predicted value. Thus, the accuracy of positioning is calculated with the Euclidean distance between the original and predicted positions.

IV. EXPERIMENTS AND RESULTS

This section presents the experiments to demonstrate the proposed indoor positioning method and compares the positioning accuracies when using a different number of SDRs.

A. Data acquisition

The experimental site was a classroom at Oakland University. The size of the classroom was 10m×12m. The SDRs should not only be away from the metal properly but also be dispersed as much as possible. The device and data acquisition setup are listed in TABLE I. The spectrums for each location of human occupation were collected from 8 pm to 10 pm. We collected 10 spectrum samples when the human subject occupied a specific location. Each sample contains 100 frequency bands.

TABLE I. DEVICES INFORMATION

Items	Iteration
Device	6× RTL-SDRs
Frequency bands	300MHz to 420MHz(step size of 1.2MHz)
Sampling rate	2.4MHz

B. Decision Tree Results

A decision tree is first applied to validate the hypothesis that human subjects occupying different locations can cause variations of passive spectrum. The passive RF spectrums at 20 human occupying positions are the input of the decision tree. The indexes of 20 positions from 1 to 20 are used as the output of the decision tree.

The cross-validation method can verify the accuracy of the model and obtain the accuracy by calculating the F1 score. The F1 score is also called goodness of fit, which is commonly used to model evaluation scales in machine learning. The function of the F1 score is as follows:

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (9)$$

$$precision = \frac{TP}{TP + FP} \quad (10)$$

$$recall = \frac{TP}{TP + FN} \quad (11)$$

$$FI = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (12)$$

In these functions, TP means true positive. FP is a false positive. FN represents false negative. TN means true negative. The FI score can only be between 0 and 1. When the value of F1 is close to 1, the accuracy of the model will be higher, and the classification result is better. When the value of the F1 score is close to 0, the accuracy of the model is low, and the classification result is worse. If the value of the F1 score is high, which indicates that there is a strong correlation between signal spectrums and human position. However, if the value of the F1 score is low, this means that it is difficult to build an accurate model between the spectrums and the location coordinates of the human subject. We also compared the impact of using different numbers of SDRs to obtain data for classification results. The classification accuracy is shown in Fig. 3.

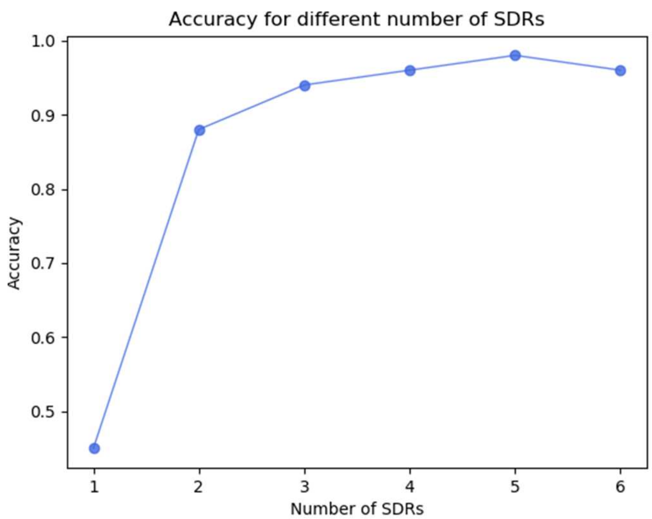

Fig. 3. The Accuracy for Different Number of SDRs.

The results show that signal spectrums can be classified by human position, and the accuracy of classification is very high. We found that when more than three devices were used for classification, the accuracy was stabilized. When using spectrums collected by one SDR, the accuracy dropped significantly. When using spectrums collected by multiple devices to train the model, the accuracy increased. These results verify that human occupancy can alter the passive RF spectrum, and human at different locations can generate different signatures on the spectrum. It also shows that using five SDRs produces the most accurate result. Therefore, this spectrum's characteristics can be utilized to achieve human positioning classification. Next, we used 4, 5, and 6 SDRs respectively to estimate the human positions.

C. GPR results

In this section, we used GPR to predict the position of test points. We selected 16 positions for GPR training and 4 positions for testing. The distributions of training and testing position are shown in Fig. 4. The red dots represent the positions of training sets, and the blue dots represent the positions of testing sets.

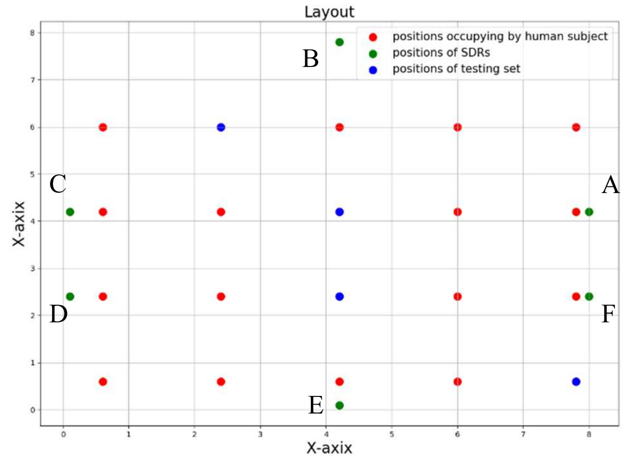

Fig. 4. The Distributions of the Training Positions and Testing Positions.

We compared the accuracy of using different numbers of SDRs to obtain spectrums for prediction results of testing human subject positions. The test results of each human occupying position are shown in Fig. 5.

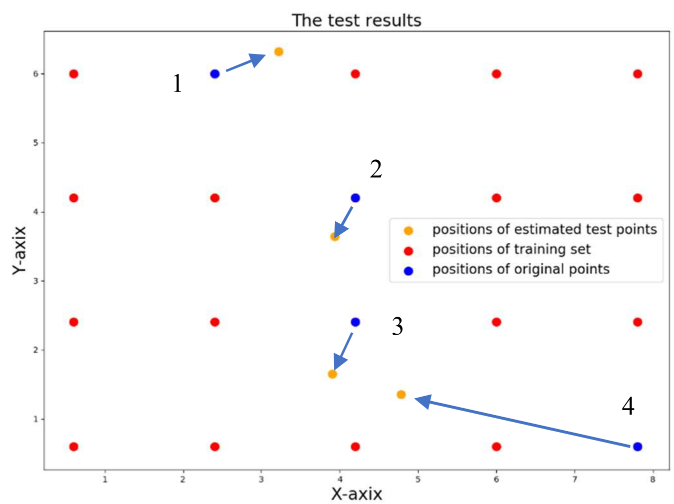

Fig. 5. The Test Results.

In Fig. 5, the red dots indicate the positions of the training set. The blue dots indicate the original position of the test point. The orange dots represent the predicted positions based on the spectrum obtained on the blue point through the GPR model. A set of orange and blue dots connected by each arrow indicates each set of original and predicted positions. The results of position 1, 2, and 3 show good accuracy, while position 4 has the worst result.

In order to obtain more detailed information and compare the effects of different numbers of SDRs, we calculated the average residuals of different test points after modeling different numbers of SDRs. The residuals were calculated using Euclidean distance between orange and blue dots. The results are shown in TABLE II.

TABLE II. RESIDUALS AT DIFFERENT POSITIONS FOR DIFFERENT NUMBERS OF DEVICES

Position	6 devices	5 devices	4 devices
1	0.837m	0.835m	0.826m
2	0.618m	0.694m	0.775m
3	0.803m	0.823m	0.852m
4	3.106m	3.108m	3.131m

In TABLE II. , the residuals calculated from the data received by six devices, five devices and four devices are separately presented. The layout of the 6 devices is shown in Fig. 4. The values of the second column are calculated by utilizing all six devices. The values of the third column are the average residuals of removing one device from devices A, C, D, and F. The values of the last column are the average residuals from the combination of device B, E, and A/C, D/F.

This table shows the residuals of different numbers of SDRs at different test positions. The prediction results for positions 1, 2, and 3 are fairly accurate. The average value of the residual is around 0.8m. However, the result of the position 4 prediction is very poor. In our experiments, when the SDRs were placed in the central area of the four boundaries, the variation of spectrum caused by the human subject at the corners are the least compared to other positions of the human subject. The behind reason needs to be explored in the future research.

The residuals of using 4, 5, and 6 devices did not have extreme change. When we used six devices, the residual results were only slightly better than using 5 and 4 devices. It shows that the residual error of positioning can be stabilized when using 4 devices.

V. CONCLUSIONS

In this paper, we verify that human occupancy can alter the passive RF spectrum, and human at different locations can generate different signatures on the spectrum. The passive RF spectrum can be utilized to achieve positioning of human subject in an indoor environment. A decision tree can classify the positions of the human on a grid with 98% accuracy using 5 SDRs. Gaussian process regression is applied to construct a model to map the passive RF spectrums and the coordinates of human locations. Using the passive RF spectrums when an unknown position is occupied by the human subject, the model can accurately estimate the human subject's location. The residual error shows that the positioning error is less than 0.8m.

The future directions of development include how to locate the human subject in a larger and open environment, to locate multiple human subjects in an indoor environment and to distinguish different human subjects in an indoor environment.

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