Room Access Management Method Using RSSI on Two Monitoring Devices from Smartphone by Machine Learning

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Abstract  This paper focuses on room access management based on the received signal strength indicator (RSSI) at two different points using two monitoring devices from smartphones. A server with a wireless LAN access point (AP) continuously sends an echo request packet to every smartphone connected to the AP, and the RSSI of the echo reply packet from the smartphones is monitored by two monitoring devices at two different points. The RSSI characteristics are that the RSSI becomes higher as the user approaches the monitoring devices and lower as the move away from them. Applying machine learning using the RSSI characteristics, we estimate the room access information of users concerning entering, staying in, or leaving the room. The proposed method does not require any special application software and user operations. Because the RSSI is monitored at two different points, our proposed method can handle various user behaviors. As a result, our proposed method achieves a high estimation accuracy of 94.44%.

Keywords: wireless LAN, RSSI, machine learning, room access management

1. Introduction

Recently, the demand for watching services for children at home or elderly people at remote locations has been increasing. To manage the behavior of such people in their living space, we expect that the demand for room access information will increase. In general, room access information has been used to improve the security of a specific facility. With the spread of the Internet of Things (IoT) and smartphones, they can be applied to a watching service for children and elderly not only in companies and facilities but also in general households [1]. However, most room access management systems require special actions such as touching an IC card reader or inputting a personal identification number in the room access control system whenever entering or leaving the room. For their introduction to general households, it is desirable that no special devices and operations are required to obtain room access information. The authors consider that a door sensor is the simplest method to detect a user entering or leaving a room, but this method cannot distinguish between a user entering and leaving the room. Our aim is to obtain room access information using a commercial wireless LAN access point, now available in most homes, and a smartphone, which most people own.

In this paper, we propose a room access management method using the received signal strength indicator (RSSI) on two monitoring devices from the wireless LAN (WLAN) of smartphones by means of machine learning estimation. In our previous studies, the effectiveness of room access estimation using RSSI on a single monitoring device was first evaluated [2]. Next, the effectiveness of room access estimation using the RSSI on two monitoring devices for handling various user behaviors was evaluated [3], and it was clarified that the estimation results do not depend on the types of smartphone [4]. In this paper, we evaluate the error rate for different user actions to supplement the previous studies.

The proposed method uses two monitoring devices for monitoring the frames from smartphones. The advantages of our method are that no special devices and user operations are required and that various user behaviors concerning entering and staying in the room can be handled.

2. Related Works

There are many methods for estimating indoor location by using the RSSI from a smartphone. In [5], Liang et al. proposed an indoor location tracking method. They used the RSSI of Bluetooth low energy (BLE) in a trilateration algorithm and some sensors embedded in the iPhone. The position was estimated by the trilateration algorithm using the RSSI from three or more preinstalled BLE beacon generators and was supplemented by geomagnetic sensor and acceleration sensor. In [6], Yang et al. developed an in-room presence detection system using the iBeacon. They used a smartphone, iBeacon installed located in the room and a motion sensor attached to the door. When the door opened, the smartphone recorded the RSSI value from the iBeacon generator and sent the RSSI value to the server, then the server estimated whether the user was in the room using the RSSI values. As mentioned above, special application software had to be installed in the smartphone.
3. Proposed Method

3.1 Overview

In this paper, we assume that the user enters, leaves or stays in the room as the user behaviors, with the user holding a smartphone which automatically connects to the AP installed in the room.

The proposed method involves a door sensor with a WLAN station, a server with a WLAN access point (AP), and two monitoring devices (M-Stations D and I). The door sensor senses the door status, which is sent to the server by the WLAN. M-Station D is set near the door, and M-Station I is set inside the room. Only using the door sensor, it can be judged that a user enters or leaves the room, but cannot be distinguished a user entering and leaving the room. The proposed method estimates whether a user is entering, leaving or staying in a room using the RSSI from the smartphone held by the user. For a specific duration after the door has been opened, each monitoring device measures the RSSI from the smartphone. Using the measured RSSI, we derive feature quantities to classify the device behaviors, with the user behaviors, i.e., entering, leaving and staying in the room, by machine learning estimation.

3.2 Door sensor

We develop a door sensor for the hinged door. The door sensor consists of a geomagnetic sensor and a small microcomputer with a WLAN device. The WLAN device acts as a WLAN station. This sensor has a function of finding the angle of door opening based on geomagnetism. As shown in Fig.1, we set the angle when the door is closed as the reference angle $\alpha$. The door sensor continually obtains the present angle $\theta$. When the difference between angle $\alpha$ and $\theta$ is larger than a specific threshold $\beta$, the door sensor judges that the door is open, and when the difference between angle $\alpha$ and $\theta$ is lower than a specific threshold $\epsilon$, the door sensor judges that the door is closed. Immediately after the door sensor judges the door is open, it sends the door status to the server. The information that the door is open is used to trigger the RSSI acquisition from smartphones.

3.3 RSSI acquisition and RSSI list

Figure 2 shows the flow of RSSI acquisition. As soon as the server receives the door status from the door sensor, the server sends an echo request packet by a ping command to all smartphones connected to the AP during duration $T$ to increase the transmission from smartphones. In addition, the server notifies each M-Station of the start and end of the acquisition of the RSSI obtained from the echo reply packets from smartphones by means of a multicast. This is because a delay occurs that depends on the number of M-Stations in case of a unicast.

We make an RSSI list of $N$ elements consisting of the mean value of the acquired RSSI in each interval of $T/N$ at each M-Station since the fluctuation of the acquired RSSI is large.
3.4 Estimation method

The proposed system estimates three types of the user behavior, i.e., entering, leaving and staying in the room, which correspond to the IN, STAY and OUT states, respectively. For classification, we define six feature quantities constructed from the RSSI lists of M-Stations, and the feature quantities from M-Stations D and I are denoted as “FD” and “FI”, respectively. Table 1 gives the feature quantities expected to be useful for estimation in the machine learning. Each feature quantity under consideration is explained in the following.

(1) FI1 and FD1

In the case of a user entering the room, the difference in the RSSI upon entering the room and after that is small. On the other hand, in the case of a user leaving the room, the difference in the RSSI upon leaving the room and after that is large, since the distance away from the door is large and the line of sight between the smartphone and monitoring devices is lost. Therefore, the difference between the mean of the starting PE partial elements of the RSSI list consisting of \( N \) elements and the mean of the ending PE partial elements can be used to classify entering (IN) and leaving users (OUT).

(2) FI2 and FD2

User staying in the room (STAY) has a smaller area of movement than a user who enters and leaves the room, so the RSSI fluctuation is small. Therefore, the variance of the RSSI list can be used to predict that the user is staying in the room. Focusing on this point, we use the variance of the RSSI list.

(3) FI3 and FD3

For FD3, since the user is near M-Station D immediately after opening the door, the mean of the PE partial elements at the beginning of the RSSI list is larger than the mean of the entire RSSI list. The RSSI list is normalized to a mean of 0 and a variance of 1 by the Z score, and the mean of the starting PE partial elements is used to predict whereas users are IN or OUT. FI3 is created to correspond to the feature quantity of M-Station D (FD3).

4. Evaluations

4.1 Evaluation environment

The door sensor consists of a small microcomputer (esp-wroom-02) with a WLAN device and a geomagnetic sensor (LSM 303 D). We set the threshold \( \beta \) to 20 degrees to judge the door opening and the threshold \( \epsilon \) to 5 degrees to detect the door closing. The server consists of a Raspberry Pi Model B+ and a WLAN USB dongle (Buffalo WLI-UC-GNM2), and the AP is constructed by hostapd. To prevent the WLAN of the smartphone from entering the sleep status, the DTIM period is set to 1 in the settings of the AP. The M-Stations consist of a Raspberry Pi Model 3 and a WLAN USB dongle (Buffalo WLI-UC-GNM2). The internal WLAN device of the Raspberry Pi Model 3 is used to communicate with the server, the WLAN USB dongle is used to monitor the WLAN data frame using tshark, and the RSSI is acquired from the data frame. Note that the MAC address of the smartphone connected to the AP is preregistered in the M-Stations, and only the WLAN data frame of the registered smartphone is acquired.

The experimental parameters are \( N=20, T=8 \) s and \( PE=3 \). We perform 144 measurements for each IN, STAY and OUT to produce learning data for machine learning. Figure 3 shows the evaluation environment for the proposed method. Table 2 gives the action contents of each user behavior and the number of trials. In addition, the persons in the room do not move and do not stand in the front of monitors except for measurement subject. There are no obstacles between the smartphone and the monitoring devices.

We use eight different smartphones: acer Liquid Z530 T02, NEXUS 5X, NEXUS 5, HTC Desire 626, FUJITSU
arrows M02, Moto G5S, ASUS ZenFone 3 and Huawei P9 lite. The k-nearest neighbor algorithm (k-NN) with k=3 is used for machine learning. The user places the smartphone in the palm of their hand facing the traveling direction. This is a practical situation, but other situations are not considered in this paper because the RSSI value will be changed by a human body effect. The machine learning is considered in this paper because the RSSI value will be changed by a human body effect. The machine learning is executed by Python with Scikit-learn [8].

### 4.2 Evaluation method and criteria

The evaluation method and criteria are as follows.

(i) Leave-one-out cross-validation

We search for combinations of feature quantities achieving the maximum estimation accuracy by leave-one-out cross-validation in the following cases: only M-Station D, only M-Station I and M-Stations D and I.

(ii) Error rate

For each maximum estimation accuracy feature quantity evaluated in evaluation (i), we evaluate the error rate, which is the ratio of the number of mistaken estimations to all estimations.

(iii) Device independence

To confirm the device independence using the feature quantity with the maximum estimation accuracy in evaluation (i), we evaluate the estimation accuracy for each smartphone using the training data excluding the data of the target smartphone for the evaluation.

### 4.3 Evaluation results

We describe the results of the above three evaluations. The result of evaluation (i) is shown in Table 3. The estimation accuracy using M-Stations D and I of 94.44% is the highest among the three cases of only M-Station D, only M-Station I and M-Stations D and I. The feature quantity for the case with the highest accuracy is the combination of FI1, FI3, FD1, FD2 and FD3. This result clarifies the effectiveness of using two monitoring devices. We also evaluate the precision, recall and F-measure by using the feature quantities with the maximum accuracy in each case for each status to confirm the estimation performance. Tables 4-6 show the precision, recall and F-measure for each feature quantity of the maximum accuracy. Each evaluation is highest using M-Stations D and I for all statuses. Therefore, the method using two monitoring devices improves the estimation accuracy in all statuses.

The result of evaluation (ii) is shown in Table 7. This table shows the error rate concerning the actual user behavior and the estimated behavior. The column (Actual behavior, Estimated behavior) indicates the actual behavior and the estimated behavior. The column shows only mistaken estimations. For example, (IN, STAY) means that the actual behavior is IN and the estimated result is STAY, which is incorrect. Comparing the cases of M-Station D and M-Station I, the error rates of (IN, STAY), (STAY, IN), (STAY, OUT) and (OUT, STAY) of M-Station D are lower than those of M-Station I. This is because M-Station D is set near the door, therefore the values of FD1 and FD3 for IN and OUT are larger than those for STAY.

Next, Fig.4 shows the distribution of each user behavior for each feature quantity. FD1 classifies three types of user behavior. Although FD3 classifies STAY, the error rates of (IN, OUT) and (OUT, IN) for M-Station I are lower than those for M-Station D. This effect depends on the feature quantities of M-Station I. In particular, F11 classifies IN...
and OUT. The error rates excluding (STAY, IN) in the case of M-Stations D and I are the lowest among the three cases of only M-Station D, only M-Station I and M-Stations D and I. It is concluded that M-Stations D and I complementarily improved the estimation accuracy. However, (STAY, IN) maintains a high error rate because the error rate is high in the case of only M-Station I.

Figure 5 shows the error rate of each ACTION using FI1, FI3, FD1, FD2 and FD3. The error rate of each ACTION is the ratio of the number of erroneous estimations to the number of trials. The error rate of ACTION7 is over 0.3. Examining the breakdown of errors, it is found that all of them were estimated to be IN. Therefore, ACTION7 is similar to ACTION1, ACTION2 or ACTION3. We assume that ACTION7 is mistaken for ACTION1 because ACTION7 is that a user moves from B to A and ACTION1 is that a user moves from the door to A. The distance from M-Station D to B is as almost the same as that from M-Station D to the door. It is considered that the fluctuation of the RSSI is very similar to each user behavior, thus the feature quantities are also similar.

5. Conclusions

In this paper, we have proposed room access management based on the RSSI at two different measurement points from smartphones. Our proposed method is capable of estimating room access information without special software and user operations. In our evaluation results, a maximum estimation accuracy of 94.44% was obtained under various user behaviors. Therefore, our proposed method can handle various user behaviors concerning entering, leaving and staying in a room. It was revealed that the estimation accuracy of room access information estimation using two monitoring devices was superior to that using a single device. Even if the data of the

| Smartphone     | Accuracy |
|----------------|----------|
| Desire 626     | 96.30%   |
| arrows M02     | 98.15%   |
| NEXUS 5X       | 94.44%   |
| NEXUS 5        | 88.89%   |
| liquid Z530    | 92.59%   |
| P9 lite        | 88.89%   |
| ZenFone 3      | 90.74%   |
| G5S            | 100.00%  |

The results of evaluation (iii) are shown in Table 8. This table shows the estimation accuracy of the device-independence evaluation. Using the feature quantities FI1, FI3, FD1, FD2 and FD3, which achieve the maximum accuracy in evaluation (i), the training data excluding the target smartphone for evaluation is used, i.e., the training data obtained from the seven smartphones excluding the target smartphone. The estimation accuracy differs for each smartphone but a value of at least 88.89% is obtained. Therefore, it is shown that the estimation accuracy is 88.89% or higher even if the data of the target smartphone used for evaluation is unknown.
target smartphone for evaluation is unknown, the estimation accuracy is at least 88.89% regardless of the smartphone. Therefore, our proposed method is applicable to various types of smartphones. Further analysis of concerning the difference between the accuracy for each smartphone is a future area of study. In addition, the evaluation in an environment where multiple humans are moving a room is also a future work. Finally, a drawback of using machine learning is that if a room is changed, the RSSI values have to be remeasured for the training data in machine learning.

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