Experimental Implementation of An Intrusion Detection System using WLAN Signals

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***Abstract*—In this paper, we experimentally implement an intrusion detection system using WLAN under the situation where many base stations are observed. Our system detects an event by measuring the received signal strength indication (RSSI) of a WLAN signal. The detection algorithm and the decision rule are presented and the effectiveness of the system is demonstrated through the measurement results.**

I. Introduction

Recently, there has been a great increase in the concern for the crime prevention security of houses, office, and cars. The current widely used security devices include surveillance cameras, vibration sensors, and infrared sensors. When the installation purpose of a security device is to detect intrusion, the surveillance camera is sometimes facing a problem of blind spots due to the limited view angle. Therefore, the installation of two or more surveillance cameras is needed to eliminate blind spots which requires additional cost. Moreover, an advanced image analysis technology or a person to keep eye on the monitor is necessary for the real-time detection of intrusion.

On the other hand, the sensor type security devices can automatically activate the alarm. The vibration sensor detects the vibration when an intruder breaks the windowpane or opens the door, while the infrared sensor detects the temperature change by measuring infrared rays or detects the infrared beam being blocked by an intruder. In either sensor type, however, the detection area is limited, and the installation location is restricted.

Against these problems, security systems that detect an indoor event by the use of electromagnetic waves are proposed [1]-[5]. Electromagnetic waves can liberate security systems from the blind spot problem by virtue of their propagation characteristics. There has been shown that TV broadcasting waves can be applied to the intruder detection systems [1]-[2]. These systems, however, sometimes are affected by events occurred outside the house such as the movement of cars.

In [3], a system employing the array antenna is presented. This system detects the intruder by detecting the arrival direction of signals. This is achieved by comparing the eigenvector of the channel observed in the stationary state with the observed eigenvector. Though the detection accuracy of the system is high, a special receiver equipped with the array antenna is required, and it is relatively expensive for the personal home use.

In [4], an intruder detection system using wireless local area network (WLAN) which is widely used at home and office is presented. By using WLAN systems, low-cost and wide-range detection can be expected without additional hardware. The system successfully detects the human movement by exploiting the discrete beacon signal of a WLAN system. However, this paper only deals with the case where only one WLAN base station is operated. There is often the case where many WLAN base stations are observed at a time, such as in condominium type residence and in SOHO (small office/home office) environment. In such a case, beacon signals may fluctuate even in a vacant room.

In this paper, we present an intrusion detection system using WLAN under the situation where many base stations are observed. Our system detects an event by measuring the received signal strength indication (RSSI) of a WLAN signal, and calculating the variance of its moving average. The detection algorithm and the decision rule are presented. Furthermore, we experimentally implement the system and show the measurement results. From the results, we can show our system effectively detects the intrusion and nearly achieves the perfect detection.

II. Fluctuations of RSSI

A. *RSSI under stationary condition*

Electric field strength of a received signal is expressed numerically as RSSI. The radiated electromagnetic waves are reflected and diffracted by various objects, and are generally received at a receiver through multiple paths. A simplified indoor propagation model between a transmitter and a receiver is shown in Fig. 1. At the receiver, the reflected and diffracted waves as well as the the direct wave are received at the same time as shown in Fig. 1; this causes multipath fading. Therefore, RSSI is slightly fluctuating even if there is no environmental change. Fig. 2 shows an example of RSSI profile observed under such an environment. In Fig. 2, the horizontal and vertical axes show the sample number and RSSI, respectively. Under the environment where there is no spatial change due to a human movement, RSSI does not change largely as shown in Fig. 2.

Next, Fig. 3 shows another simplified propagation model in which some of the propagation paths are blocked by an obstacle. In Fig. 3, the direct path is blocked because an obstacle exists between a transmitter and a receiver. In such

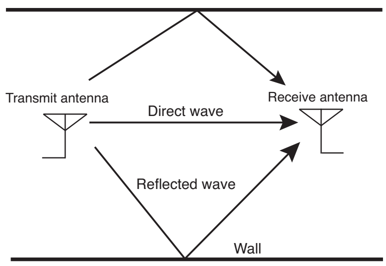

Fig. 1. Propagation model.

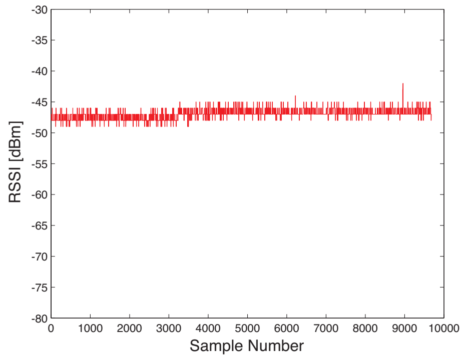

Fig. 2. RSSI profile of the stationary state.

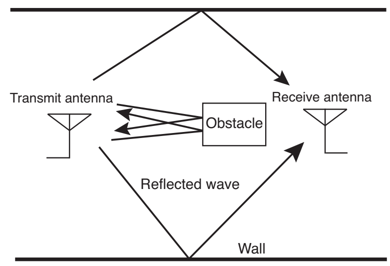

Fig. 3. Propagation model without direct path.

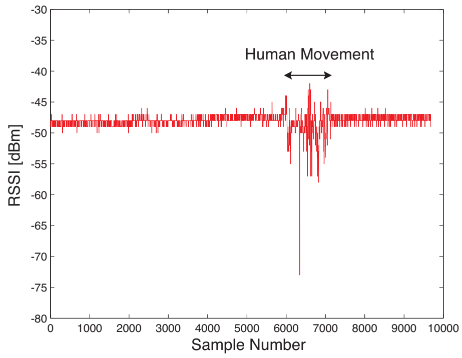

Fig. 4. RSSI fluctuations by human movement.

a case, the value of RSSI becomes small. In particular, the change in the indoor spacial environment that is originated with the human activity greatly changes RSSI because it changes the propagation paths of signals.

Fig. 4 shows an example of RSSI profile observed when a person enters a room. In Fig. 4, irregular changes of RSSI can be noticed between the 6,000th and the 7,000th samples where person's motion of entering and leaving a room is conducted. Therefore, it can be said that a person becomes an obstacle to the receiver, and the fluctuation of RSSI due to the human movement is distinguishable from that of the stationary state.

B. RSSI under coexistence with other systems

The frequency band used for WLAN is a licence free band called ISM (industrial, scientific and medical), and is also used for many communications applications, including Bluetooth and ZigBee. Microwave ovens also use this frequency. Therefore, RSSI of WLAN signals is influenced by the operations of the other systems even if there is no spacial change due to the human movement. In addition, a lot of WLAN base stations might be set up in a narrow area such as condominium type residence, SOHO environment, and schools.

In IEEE 802.11 WLAN standard, 2.4-GHz ISM band is partitioned into thirteen channels each of which has a bandwidth of 22 [MHz] and is separated by 5 [MHz]. Fig. 5 shows the channels defined in IEEE 802.11. From Fig. 5, it can be seen that adjacent channels overlap. Therefore if there are pieces of WLAN equipment that need to work on non-interfering channels, there is only a possibility of three. In most cases, however, one might set up a WLAN base station independently without considering the neighboring WLAN systems. Furthermore, when more than four WLAN systems are set up within a narrow area, the frequency overlap is unavoidable. In such cases, signals of different WLAN systems interfere with each other; this also causes RSSI fluctuations.

Fig. 6 shows an example of RSSI profile under the environment where many WLAN systems are operated at neighboring rooms/floors. Within the samples encircled by the short dashed line in Fig. 6, there is no human movement. Therefore, we must distinguish the RSSI fluctuations caused by the human movement from those caused by the other factors. In this paper, we propose a detection algorithm of the person's movement of entering a vacant room for a security purpose. The next section describes the detection algorithm.

III. Detection Algorithm

In this paper, we propose a intrusion detection method that uses the variance of the moving average of RSSI. By using the moving average, an irregular change of RSSI can be smoothed. Fig. 7 shows the result of the moving average of the RSSI profile shown in Fig. 6. Here, since the unit of RSSI is dBm, the moving average is calculated in the unit of watt. Fig. 7 (a) is the result of 10-sample moving average, and Fig. 7 (b) is that of 100-sample moving average. It can be seen that the sudden change around the 1,500th sample is mitigated by enlarging the number of averaging samples. However, there is a possibility that the change of RSSI due to intrusion becomes also small when the number of data samples used for the moving average is increased. Therefore, it is necessary to carefully choose the number of data samples used for the moving average.

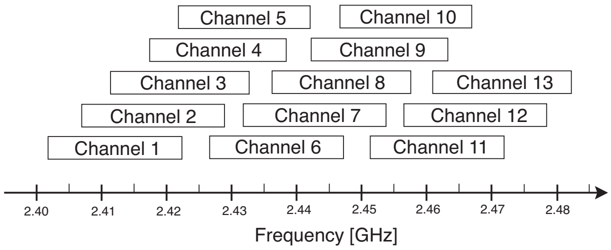

Fig. 5. Channel of IEEE 802.11g

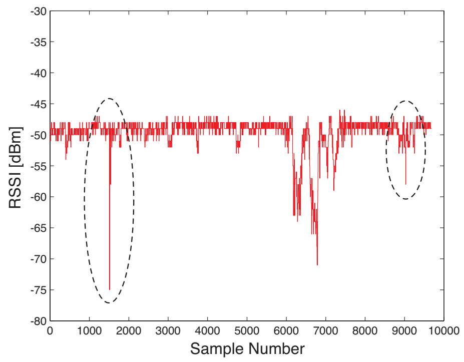

Fig. 6. RSSI fluctuations by other factors.

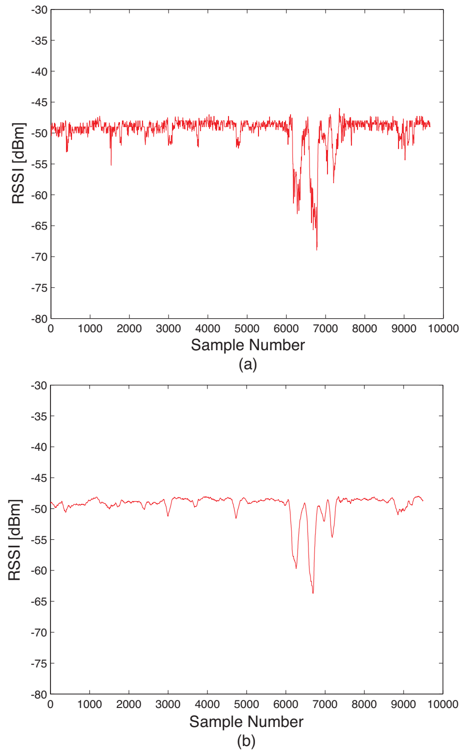

Fig. 7. RSSI profile after moving average processing: (a) 10-sample moving average, (b) 100-sample moving average.

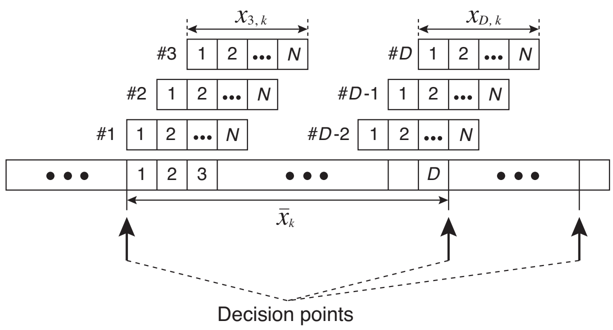

Fig. 8. Detection algorithm.

A generalized schematic diagram of the algorithm proposed in this paper is illustrated in Fig. 8. In Fig. 8, D is the number of data samples to calculate a long-term average value of RSSI in watt which is required for calculating the variance of the moving average. The average value of the k-th long-term averaging interval is denoted by $\bar{x}_k$. N is the number of data samples to calculate a short-term moving average of RSSI in watt. The i-th moving average within the k-th long-term averaging interval is denoted by $x_{i,k}$. Hence, the variance of $x_{i,k}$ is denoted as V_k, and is given by

$$V_k = \frac{1}{D}\sum_{i=1}^{D}(x_{i,k} - \bar{x}_{k-1})^2. \tag{1}$$

Decision rule whether an intruder breakes into a room is defined as

$$\frac{V_k + V_{k+1}}{V_{k-2} + V_{k-1}} > W, \tag{2}$$

where W is the decision threshold. Since irregular fluctuations of the variance appear in very short time, the use of Eq.(2) can mitigate the false alarm.

IV. Experimental Results

In this section, we present some experimental results. Rooms used for experiment are our laboratory in Chiba Institute of Technology, Narashino, Japan. Figs. 9 and 10 show the rough sketches of the rooms. The size of Room 1 in Fig. 9 is 7.0×8.6 [m^2]. The size of Room 2 is 5.1×8.6 [m^2] in Fig. 10. From figures, Room 1 is more crowded with furniture and computers than Room 2. Table 1 shows the experimental parameters. Tx and Rx (two positions) in Figs. 9 and 10 are a commercial WLAN base station and laptop receivers each of which is set up at a height of one meter.

Here, it should be noted that more than six WLAN access points of other laboratories within the same building were observed from the laptop used to experiment at the time of the experiment. Since we are not authorized to access those access points, it was uncertain whether their clients were connected to those access points at the time of experiment. Furthermore, we employed IEEE 802.11g WLAN standard in the experiment instead of the latest IEEE 802.11n. IEEE 802.11n employs the multiple-antenna technology, and we cannot explicitly specify the transmission mode (such as the number of transmit/receive antennas) in the commercial equipment. Thus, we used IEEE

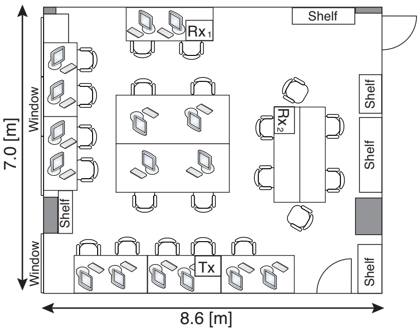

Fig. 9. Rough sketch of Room 1.

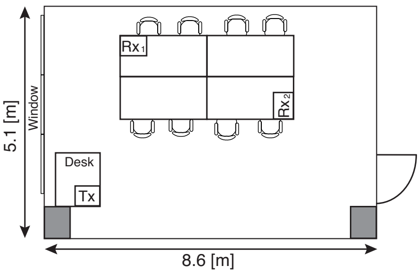

Fig. 10. Rough sketch of Room 2.

802.11g because the use of IEEE 802.11n might be another ambiguous factor in exploring of our system.

Figs. 11 to 14 show the experimental results. Figs. 11 and 12 show the results obtained in Room 1, and Figs. 13 and 14 are those in Room 2. In each figure, (a) is the observed RSSI profile, and (b) to (d) are the variance obtained using Eq. (1) with various parameters. In the experiment, a person enters the room at around the 6,000th sample, then moves constantly before leaving the room at around the 7,000th sample. Since the observation sampling rate is 55.5 [sample/sec], the human movement is conducted between about 108 to 126 [sec].

First, we consider the difference between the results of Room 1 and those of Room 2. The RSSI observed in Room 1 presents a larger number of irregular fluctuations than that in Room 2. Since Room 1 is more crowded with furniture and computers than Room 2, more complicated paths are established in Room 1 which is susceptible to interference. In our system, it is decided that the human movement occurred when the value of the variance becomes high. Thus, the number of objects within the room affects the detection performance, and the intrusion detection is more difficult in Room 1 than in Room 2.

Next, we consider the selection of the parameters in Eq. (1). From the figures, it can be seen that the change of the variance due to the human movement in Fig. 11 is less distinguishable than those in the remainder figures. Thus, we focus on Fig. 11 for the parameter selection. In our system, the value of the long-term averaging interval D dominates the decision interval as shown in Fig. 8. In this experiment, the decision is made every 1.8 [sec] when $D = 100$, every 5.4 [sec] when $D = 300$, and every 9 [sec] when $D = 500$. When D is small, the immediateness of detection becomes high at the cost of a high probability of false detection. From the figures, the change of the variance due to the human movement is more distinguishable when $D = 500$. For the intrusion detection, 9 [sec] is quick enough. Thus, we employ $D = 500$.

In the meantime, the short-term moving average interval N does not largely affect the detection performance. However, the value of N affects the memory size for calculation. Thus, we adopt the parameters as $N = 50$, and $D = 500$ hereafter.

Finally, we consider the threshold in Eq. (2). Fig. 15 shows the threshold value versus the false alarm rate/the missed detection rate. In Fig. 15, the false alarm rate is defined by

$$P_{\mathrm{FA}} = \frac{N_{\mathrm{FA}}}{N_{\mathrm{Total}}}, \tag{3}$$

where N_{Total} is the total number of the variance samples during the observation, and N_{FA} is the number of variance samples whose values exceed the threshold though no intrusion occurs. Moreover, the missed detection rate is defined by

$$P_{\mathrm{MD}} = \frac{N_{\mathrm{MD}}}{N_{\mathrm{Total}}}, \tag{4}$$

where N_{MD} is the number of variance samples whose values does not exceed the threshold though an intrusion occurs.

In Fig. 15, we can perfectly detect the intrusion when the threshold W is between 9 and 15. In our environment, we can

TABLE I
EXPERIMENTAL PARAMETERS.

WLAN standard	IEEE 802.11g
WLAN channel	Channel 13 (2.461 to 2.483 [GHz])
Sampling rate	55.5 [samples/sec]
Number of samples, D	100, 300, 500
Number of samples, N	10, 50, 100

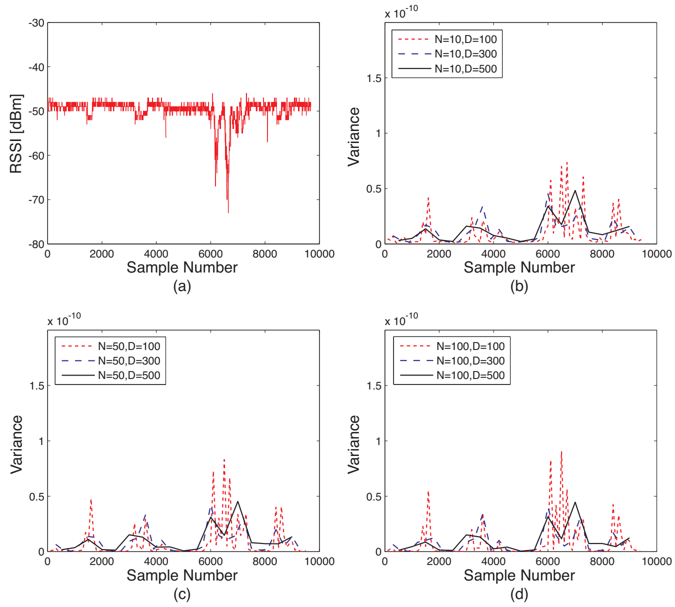

Fig. 11. Results of Rx_1 in Room 1.

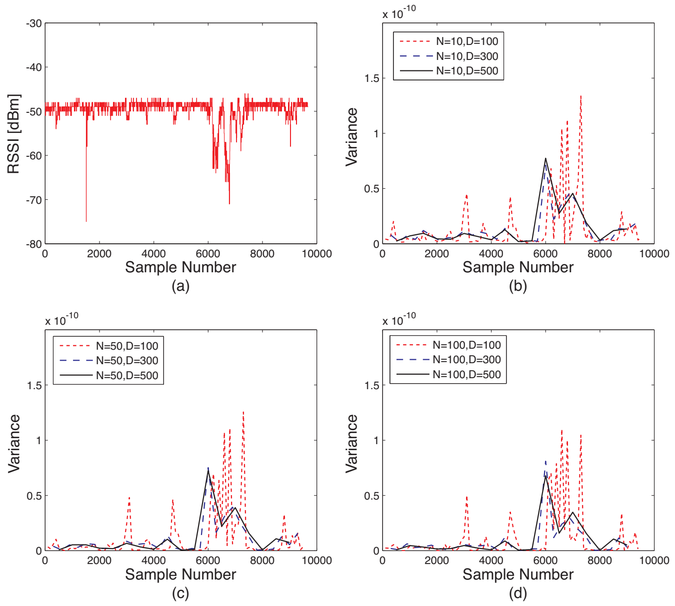

Fig. 12. Results of Rx_2 in Room 1.

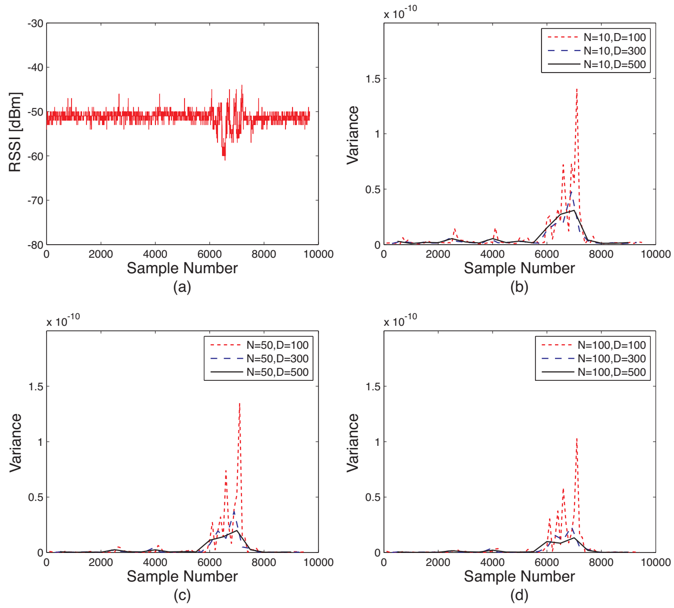

Fig. 14. Results of Rx_2 in Room 2.

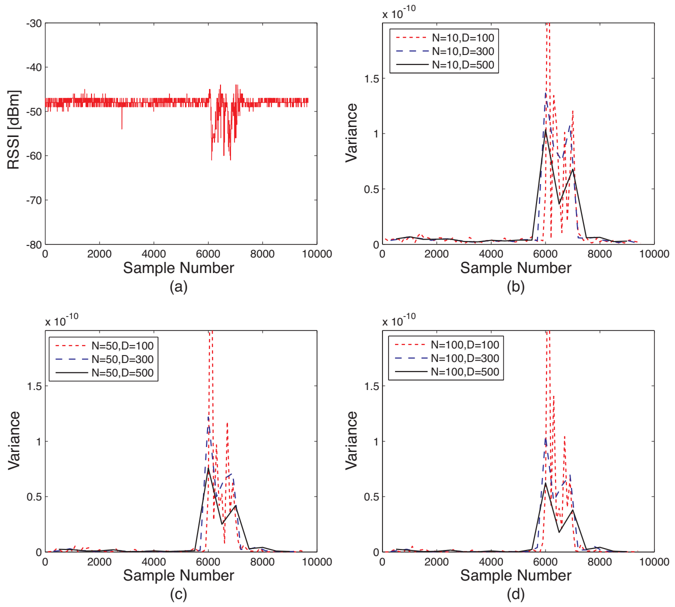

Fig. 13. Results of Rx_1 in Room 2.

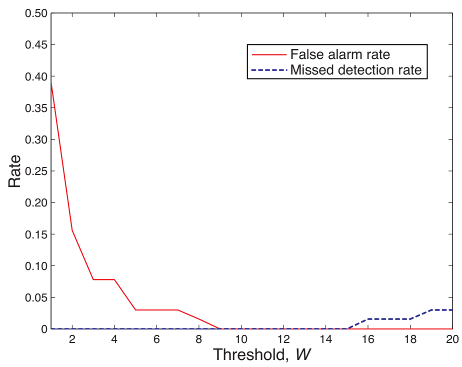

Fig. 15. Threshold versus various rate.

perfectly detect the intrusion when $W = 12$. Thus, our system is very effective for intrusion detection.

V. Conclusions

In this paper, we have presented an intrusion detection system using WLAN under the situation where many base stations are observed. Our system detects an event by measuring RSSI of the received WLAN signal. The detection algorithm and the decision rule are presented, and the effectiveness of the system is demonstrated through the measurement results. We have experimentally implemented an intrusion detection system and demonstrated that our system nearly achieves the perfect detection. In the future, we try to examine systems using IEEE 802.11n.

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