Calibration-Free Wireless-LAN Location Estimation System Using Polar Coordinates Filter

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***Abstract*— Many means exist to estimate a person's position using Wireless-LAN. Conventional methods require a large amount of data which is previously measured for calibration, however. This research aims for calibration-free position estimation. We make use of polar coordinates to make estimation without calibration and propose an estimation algorithm. s show the usefulness of our algorithm. And we also improve accuracy of real time location estimation by using polar coordinate filter.**

***Keywords*— Wireless-LAN, Location estimation, RSSI, polar coordinates**

1. Introduction

Nowadays a method to precisely estimate indoor location is demanded. In indoor environments, there are many obstructions leading electric wave to reflection, diffraction and attenuation. Thus it is difficult to estimate person's position precisely by only electric wave like Wireless-LAN. Recently, however, there are several ways of approaching this problem by filtering Wireless-LAN data.

Bahl, et al. [1] proposed the RADAR method. This method estimates person's position from alteration of plural signal strengths which obtained from Wireless-LAN access points. They showed this method can theoretically decrease a margin of error. Alippi, et al. [2] reported a way to improve person's position accuracy by learning estimated positions of unknown access points in an environment.

On the other hand, Rekimoto, et al. [3] proposed another way to estimate person's position using a database which collects signal strengths and location information. This method uses signal strengths' information which is already reflected, diffracted and attenuated. It enables them to precisely estimate person's position.

These researches request, however, a large amount of data which is previously measured for calibration. If we used these methods without calibration, person's position could not be estimated precisely. For example, complicated calibration sometimes hindered from introducing location information to service applications. Temporary event space especially hard to use location information, cause conventional methods' calibration cost are not balanced their benefits in short terms.

Our approach aims to show the same degree of accuracy as conventional methods without calibration. In this paper, we show the calibration-free location estimate method. This method does not use usual minimum mean square error heuristic when estimated position is near from access points and enables to estimate position precisely without calibration data.

And our research suggested another problem in Wireless-LAN location estimation. Conventional researches are hard to use in real time location estimation. This problem originates in Wireless-LAN network system, explained minutely in section 5. We showed polar coordinates filter approach is effective also in real time estimation.

There are 7 sections in this paper. In section 2, we explain the characteristic of Wireless-LAN and verify the characteristic. Section 3-4 give an explanation algorithms of polar coordinates filter which is our original method and a result of an experiment. From section 5, we mention about real time location estimation.Section 6 indicates simulation result of real time location estimation. Finally we make a summary of these methods in section 7.

2. Characteristic of Wireless-LAN

Wireless-LAN electric wave's characteristics were investigated[1]. They showed a signal strength decreases exponentially with distance. When a receiver obtain data d [m] away from an access point, the signal strength $S(d)$ [dBm] is represented by the following equation from the characteristic:

$$S(d) = 10n\log(d) - R, \tag{1}$$

where n is a constant number according to the maximum output of the access point, R is a constant number according to the maximum resolution of the network interface device which receives electric wave. We verified the correctness of this formula just to make sure that this formula is theoretical and Wireless-LAN standards are mainly changed from IEEE 802.11b to IEEE 802.11n.

We measured relationships between distance and signal strength by using four access points. These access points are the same model. From these relationships, we performed an exponential regression analysis for each access point. Table1 shows the results of regression analysis of each access point. Each and every access points reported a high correlation, correlation coefficients are about 0.8. All regression equation were much the same.

3. Determination of Position Coordinates

Generally, position of the receiver is uniquely determined by the minimum mean square error (MMSE) method converting distance from each point of access points to signal strength [4]. Here the MMSE method has been used as a maximum likelihood method, which also played a role of filtering.

When we use the MMSE method, especially in location estimation, we usually set a weight for each access point. To determine a weight, however, plenty of calibration data are required.

To realize a calibration-free method, we improve estimated position accuracy without Weighted-MMSE.

We determine the receiver position $P(x_p, y_p)$ by the following algorithm, where S_1 is the maximum signal strength from all access points, $AP_1(x_1, y_1)$ is the access point which have signal strength S_1, and S_0 is the threshold.

1) If $S_1 \leq S_0$, we determine the receiver position by the MMSE, or else we determine it by the following steps.
2) Set r-θ polar coordinates where the origin is (x_1, y_1).
3) Transform S_1 to d_1 which is the distance between AP_1 and P using 1) Then set $r = d_1$.
4) Determine the temporal device position $P_{temp}(x_t, y_t)$ by the MMSE method. We use θ_{temp}, which obtains from P_{temp}, as approximation of θ, thus we determine $\theta \approx \theta_{temp}$.
5) From step2 to step4, we obtain $x_p = x_1 + r\cos\theta$ and $y_p = y_1 + r\sin\theta$.

Fig.1 shows concept of the Weighted-MMSE and Our Algorithm.

Table 1. The result of experiment

AP	Regression Equation	Correlation Coefficient
1	S(d) = -8.03log(d) -31.15	0.80
2	S(d) = -8.32log(d) -27.99	0.83
3	S(d) = -8.16log(d) -28.14	0.81
4	S(d) = -8.12log(d) -30.40	0.81

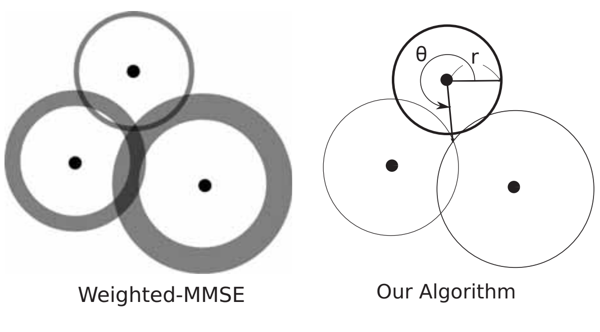

Fig. 1. Concept figure of the Weighted-MMSE and Our Algorithm

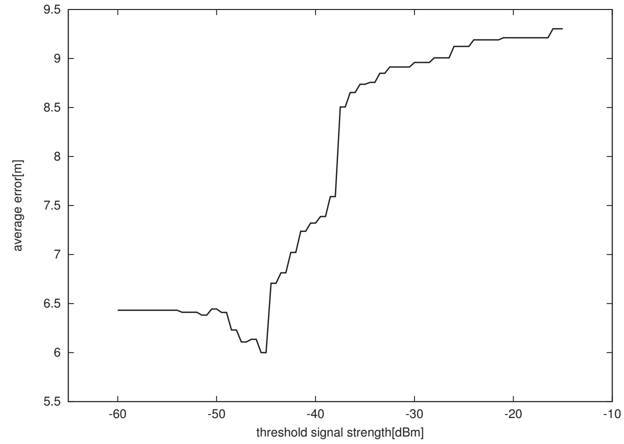

Fig. 2. Relationship between threshold signal strength and average error

Table 2. Comparison among algorithms

	MMSE	Weighted-MMSE	Proposed method
Average Error[m]	12.37	10.44	6.00
Standerd Deviation[m]	10.58	7.71	4.68

4. Experiment of polar coordinates filter

In this experiment, we measured four signal strengths and position coordinates, then converted signal strength to estimated position by the MMSE, the Weighted-MMSE and our method. We compared estimated position with real position. Weights of the Weighted-MMSE algorithm was decided on condition that according to data which were obtained in pilot survey.

Before we compare these three algorithms, we also determined the most suitable value of the threshold S_0 by moving S_0 and comparing average error.

We used four AirStation WZR-HP-G300NH as access points and a PC as a receiver. The spec of PC is following: OS:Windows XP, CPU:Atom N270 1.6GHz, Memory: 2GB, NIC:Atheros AR5007EG Wireless Network Adapter.

Experiments were performed in a large room: the hall at The University of Tokyo. The floor space is 21[m] by 18[m]. Then we set the measurement area 20[m] by 16[m] rectangle and placed access points on each corner. Measurement points are set per 2[m] grid points and measured signal strength 100[times] at every points.

We calculated the minimum average error in the proposed algorithm while changing threshold S_0's value by 0.5[dBm]. The result is shown in Fig.2. The smallest average error was obtained when signal strength equals -45[dBm] from the figure.

Table2 is a comparison chart among three methods. Both average error and standard deviation of our method are better than MMSE and Weighted-MMSE. This result indicates the usefulness of the proposed method.

5. Combination of particle and polar coordinates filter

One of the most difficult problems when we estimate a person's position with Wireless-LAN is the length of measurement interval. To measure multiple access points' signal strengths, we must wait at least six seconds to collect signal strengths information, cause network interface card (NIC) need time to collect all access points' information. In less than six seconds, we can only know one access point signal strength every second which is connecting. These feature mean that we can't obtain estimated position without waiting every six second. For some applications, which require position information in real time, the interval is too long to use.

To solve this problem and improve the accuracy of real time position estimation, we suggest a combination of polar coordinates filter and the particle filter. The algorithm of our combination filter is following.

It is well known that the particle filter is a kind of filter which revise estimated position by considering time series information[5]. Now we present a brief description of the particle filter algorithms and how we combine polar coordinates filter to the particle filter.

Commonly, particle filters execute a four-step process in relation to one observed datum: resampling, forecasting, assigning importance, and position estimation.

In the resampling step, particles are chosen according to their importance, as decided in the assigning importance step. Only at the first time, particles are uniformly arranged in an area. By this step, particle positions $Q^{(1)} \sim Q^{(M)}$ are determined uniquely as (2).

$$Q^{(i)}(x^{(i)}, y^{(i)}) \qquad (i = 1, \cdots, M) \tag{2}$$

The forecast step moves particles according to the state function. Particle positions at k-th step moves as (4) if state function is described as (3), where M is a number of particles.

$$(x_n, y_n) = f(x_{n-1}, y_{n-1}) \tag{3}$$

$$Q_k^{(i)} = f(Q_{k-1}^{(i)}) \qquad (i = 1, \cdots, M) \tag{4}$$

In this paper, the state function is decided on condition that particles move randomly inside a circle. Because people generally move arbitrarily within a room, but their walking speed are functionally limited. Therefore, we decided to change the circle's radius in proportion to the measured interval.

Assigning importance step is to determine each particle's plausibility. Plausibility is commonly determined by the distance from particle to the observed position $O_k(x_k^o, y_k^o)$ as (5).

$$w(Q_k^{(i)}) = \sqrt{(x_k^{(i)} - x_k^o)^2 + (y_k^{(i)} - y_k^o)^2} \qquad (i = 1, \cdots, M) \tag{5}$$

We combine polar coordinates filter in this step. When we can't obtain enough datum to calculate estimated position by MMSE and can't determine estimated position $O_k(x_k^o, y_k^o)$, we assign importances by polar coordinates. If only one signal strength from $AP_1(x_1, y_1)$ can obtain, importance is decided by observed the signal strength S_1 as (6), where d_1 is distance between access point and device. d_1 is settled by S_1 and (1).

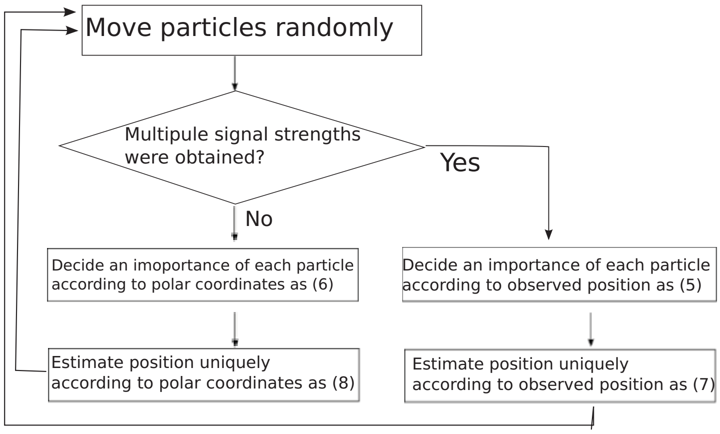

Fig. 3. Flow chart of the combination filter

$$w(Q_k^{(i)}) = \sqrt{(x_k^{(i)} - x_1)^2 + (y_k^{(i)} - y_1)^2} - d_1 \quad (i = 1, \cdots, M) \tag{6}$$

Finally, the position estimate step determines the decide estimated position $E_k(x_k^e, y_k^e)$ uniquely considering all particles. Here we take the average of all particles as (7).

$$E_k(x_k^e, y_k^e) = \Big((1/M)\sum_{i=1}^{M} x_k^{(i)}, (1/M)\sum_{i=1}^{M} y_k^{(i)}\Big) \tag{7}$$

However, this equation is not appropriate when plausibility was decided as (6). We should take average after converting x and y to r and θ because particles scatter according to polar coordinates as (8).

$$\begin{aligned} Q^{(i)}(r^{(i)}, \theta^{(i)}) \quad (i = 1, \cdots, M) \\ r^{(i)} = \sqrt{x^{(i)} + y^{(i)}}, \theta^{(i)} = \arccos(x^{(i)}/r^{(i)}) \end{aligned} \tag{8}$$

Then we can decide estimated position as (9).

$$\begin{aligned} E_k(x_k^e, y_k^e) = \big(r_{ave}\cos\theta_{ave}, r_{ave}\sin\theta_{ave}\big) \\ r_{ave} = (1/M)\sum_{i=1}^{M} r_k^{(i)}, \theta_{ave} = (1/M)\sum_{i=1}^{M} \theta_k^{(i)} \end{aligned} \tag{9}$$

These steps organize the combination filter. The flow chart of these steps is Fig.3.

Fig. 4 shows the graphical image of the combination filter. Only one signal strength is not enough to decide estimate position, however it even affect as a binding condition for particles.

6. **Experiment of combination filter**

We did an experiment to confirm this combination filter performance. The environment is same as the environment which is mentioned in section4. There are four access points and we can obtain all of their signal strengths every six seconds, connected access point's signal strength can obtain

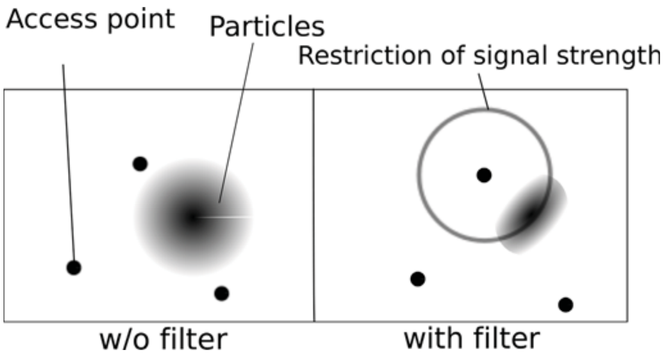

Fig. 4. Affect of binding condition

Table 3. Comparison filters when moving speed is 2[m/s]

	Particle filter	Combination filter
Average Error[m]	18.31	9.46
Standard Deviation[m]	18.26	3.67

every one seconds. Combination filter use both information and particle filter only use every six seconds information.

In general, a person walk at a speed of 1-2 meters per second. Thus we experimented walking speed in 2[m/s]. We walked 10 times according to the way like Fig. 5 and calculated average error and standard deviation.

Table3 is a comparison chart between particle filter and combination filter. You can easily understand that combination filter enables more correct location estimation than the particle filter.

7. Conclusion

The results of this study suggest an effective way to estimate position without calibration. And the combination of the particle filter and polar coordinates filter shows the effective way to estimate position in real time tracking. These two experiments indicate that using polar coordinates to Wireless-LAN location estimation is useful to improve accuracy. In the future, to further improve the accuracy, we need to consider environmental information.

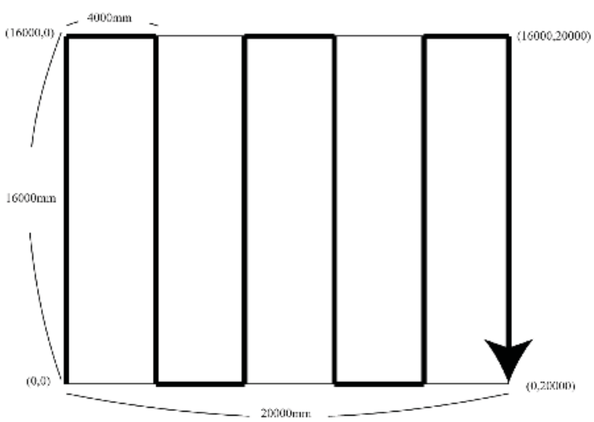

Fig. 5. Walking root in experiment

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