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Filter Design by Using Map Information on Wireless-LAN Location Awareness System

Jun Ishii, Yusuke Tamura and Hajime Asama
Research into Artifact, Center for Engineering (RACE)
The University of Tokyo
5-1-5 Kashiwanoha, Kashiwa-shi, Chiba 277-8568, Japan
j-ishii@race.u-tokyo.ac.jp

***Abstract*— Technologies to identify people and determine their positions are developing rapidly day by day. Many means exist to estimate a person's position. Mainly, wireless sensors are used. Nevertheless wireless sensors have problems in accuracy. Because of multipath problem, wireless sensors cannot actually measure one's position as the level of their specifications. This causes some fatal problems to estimate an area where person is. In this paper, we present a way to improve position information by filtering data which was obtained by a wireless location awareness system. We also show designed filter which is based on particle filter is effective by simulations and experiments.**

***Index Terms*— Location awareness, Particle filter, Visibility graph, Time difference of arrival**

I. INTRODUCTION

Location technology are developing daily. They have become capable of measuring one's position and personal information more correctly and their cost has become lower than before. Locatoin technology enable us to supply high-quality services on demand.

One of the representative example is Global Positioning System. GPS technology is used in many places and by many devices. Car, cellular phone, note PC and more. It means location technology is definitely needed.

Now we consider services using wireless sensors. Wireless sensors are now frequently used in location awareness services because they can be used in a wide area and many can easily identify a person using information transmitted by radio waves. As described later in related works, RFID sensors are one good example.

We presume that these sensors are used at a complicated partitioned indoor place such as a shopping mall or department store. In such places, it is necessary to detect a partition in which a person is present and the person who he is. If these things can detect, services and infomation can meet the demand at a high quality.

Conventional location awareness systems are filtered by one-dimensional restrictions. Various devices can provide location awareness services using wireless systems. Actually, as I mentioned before, GPS is the most used device. Researchers have attempted to improve the accuracy of GPS estimates. White et al. [1] showed that the use of map information to correct the estimated position is definite effective to improve accuracy. Furthermore, Greenfeld [2] suggested the way to make the White algorithm more adequately fit the real position. These works are not useful in presumed case, however. This fact means that conventional filtering cannot be used in a situation such as that shown in Fig. 1. The estimated position could not be decided uniquely if we applied a one-dimensional restricted filter, as shown in the right side of the figure.

Recently RFID, Wireless-LAN and Bluetooth systems have often been used. These systems have the merit of being able to identify personal information, whereas GPS cannot. It can be said that these systems better supply service on demand than GPS does. Feldmann et al. [3] described that the strength of radio waves used with Bluetooth devices enables us to estimate positions of the devices. Rekimoto et al. [4] reported a way to estimate a position by Wireless-LAN access point signal strength. Many studies using RFID have been published because RFID costs have decreased rapidly. In fact, Hähnel et al. [5] and Ni et al. [6] established the basis of RFID position estimation.

In addition, services by position estimation are sometimes investigated for their value. Especially noteworthy is that Bohnenberger et al. [7] showed that people in a shopping mall got more satisfaction when they were given information of position and guided to a destination than without.

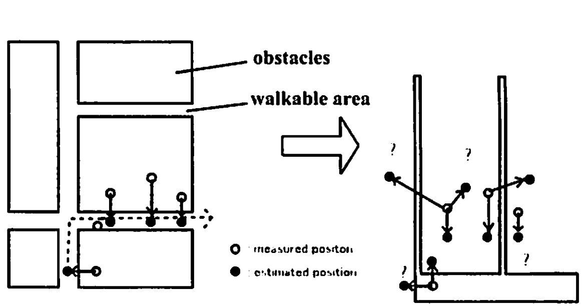

Fig. 1. Apply one-dimensional restricted filter to two-dimensional area

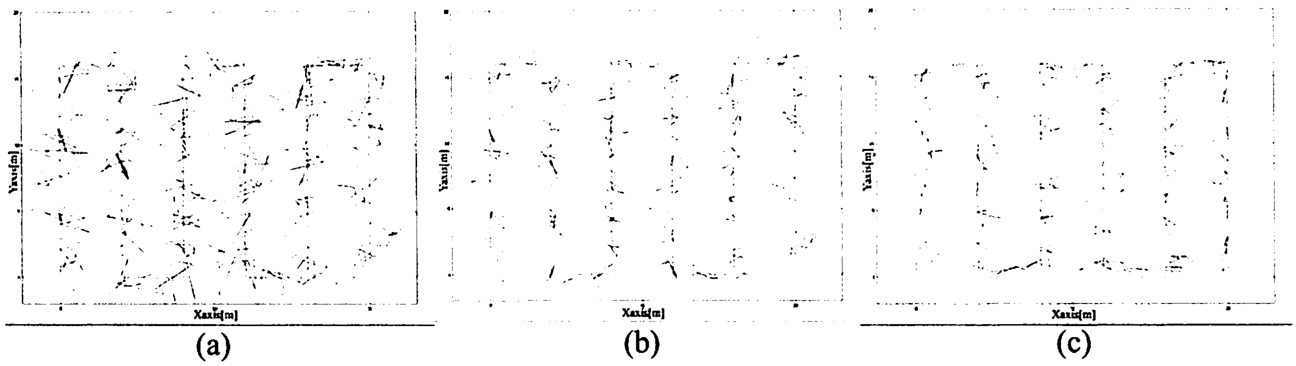

Fig. 2. Figure of simulation. (a) is a normal distribution noise-simulated route, (b) is a estimated route by extended Kalman filter and (c) is a estimated route by particle filter. A real route is showed by a broken line in (a), (b) and (c).

II. FILTER DESIGN

When we use wireless sensors, we should use appropriate filtering and cut their noise. In contrast to wired sensors, wireless sensors give us data that are too noisy because wireless sensors have a multipath problem. Reflected or diffracted radio waves interfere with original waves. Thereby, their accuracy is degraded.

A. *Extended Kalman filter and particle filter*

First, we specifically examined filters of two kinds: an extended Kalman filter [8] and a particle filter [9]. These filters are frequently used to estimate position. Of course, numerous studies have been undertaken to improve accuracy using these filters.

To confirm these filters' performance, we simulated whether these filters improve accuracy of the estimated position. We presumed that humans are walking in a large room and that a wireless sensor periodically measures one's position. Noise was generated and added to the real position to simulate a multipath situation. We also presumed that noise follows a normal distribution which average is 0[m] and standerd deviation is 1[m]. We processed these data using each filter and compared the calculation time, average error, and standard deviation. In article filter, the number of perticles set for the particle filter is 100. The result is presented in Fig. 2 and Table I. Both filters can reduce the average error and standard deviation.

However, fatal problems exist in this result. They can be illustrated best using extreme cases. In Fig. 2, if a space was partitioned by wall between $(x, y) = (8.1, 0)$ to $(8.1, 15)$, then the partition might be detected wrongly many times around the wall, even after filtering. Therefore, other means must be considered to improve the estimated position in a presumed situation.

TABLE I

RESULT OF SIMLATION

	calculation time per datum [s]	average error [m]	standerd deviation [m]
(Without filter)	N/A	1.18	0.63
Extended Kalman filter	0.005	0.91	0.51
Particle filter	0.15	0.83	0.45

B. *Adding map information*

As described in a related work, filtering by map information is also useful for position estimation. In presumed situation, however, it is not enough only to use map information for filtering. For that reason, we consider adding map information to the particle filter. Two main reasons can explain why we use the particle filter. The two filters differ widely in that the particle filter is non-parametric and the extended Kalman filter is parametric. Consequently, the particle filter is more easily added to map information for algorithms than an extended Kalman filter is. Furthermore, it is presumed that multi-path noise does not always follow a normal distribution. From that perspective, parametric filters also present advantages. Therefore, we decided to use a particle filter.

1) Particle filter algorithms: Before explaining how to add map information to a particle filter, we present a brief description of particle filters. 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 choosen according their importance, as decided in the 'assigning importance' step. Only the first time, particles are uniformly arranged in an area. By this step, particle positions $Q^{(1)} \sim Q^{(M)}$ are determined uniquely as (1), where M is a number of particles.

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

The forecast step moves particles according to the state function. Particle positions at k-th step moved as (3) if state function was described as (2).

$$(x_n,y_n) = f(x_{n-1},y_{n-1}) \tag{2}$$

$$Q_k^{(1)} = f(Q_{k-1}^{(1)}),Q_k^{(2)} = f(Q_{k-1}^{(2)}),\cdots,Q_k^{(M)} = f(Q_{k-1}^{(M)}) \tag{3}$$

For examination in this paper, particles move randomly inside a circle. People generaly move arbitrarily within a room, but their walking speed are effectively limited. Therefore, we decided to change the circle's radius in propotion 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 (4).

$$w(Q_k^{(1)}) = \sqrt{(x_k^{(1)}-x_k^o)^2+(y_k^{(1)}-y_k^o)^2}$$
$$\cdots$$
$$w(Q_k^{(M)}) = \sqrt{(x_k^{(M)}-x_k^o)^2+(y_k^{(M)}-y_k^o)^2} \tag{4}$$

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 (5).

$$E_k(x_k^e,y_k^e) = ((1/M)\sum_{i=1}^{M}x_k^{(i)},(1/M)\sum_{i=1}^{M}y_k^{(i)}) \tag{5}$$

These four steps organize the particle filter.

2) Adding visibility graph algorithms: We next specifically examine assigning importance step. In particle filter, the plausibility is generally determined by Euclidean distance. Euclidean distance is not always correct to determine plausibility however. For example, obstacle between previous step position and present step position exists, two possibility can think about present step estimation. One is that the present step position and previous step position is same side of the obstacle in essence, but accidentally present step position was estimated the other side of the obstacle cause of multipath problem. Another is that a person walked around the obstacle and that the present step position is correct. The latter possibility can be expected to be lower for larger obstacles because a person must move around the obstacle to cross. Therefore, we suggest expressing the importance by the shortest distance considered as obstacles between two steps.

In mobile robotics, many solutions are suggested to find the shortest path in a place with many obstacles. From these solutions, we use a visibility graph method [10] . This method is effective in two-dimensional space. Below are proceedings of visibility graph method.

(a) Set nodes of the graph on vertices of obstacles and the start node and the goal node. In Fig. 3, $A \sim F$ are nodes.
(b) Link nodes which are visible to each other. Whether $A(a_x,a_y)$ and $B(b_x,b_y)$ are visible can be decided by endpoints of segments structured by the surface of obstacles such as $C(c_x,c_y)$ and $E(e_x,e_y)$. When both (6) and (7) are satisfied, segment AB and segment CE intersect. Consequently, A and B are not visible to each other.

$$(a_y-b_y)(c_x-a_x)-(a_x-b_x)(c_y-a_y)\cdot$$
$$(a_y-b_y)(e_x-a_x)-(a_x-b_x)(e_y-a_y) \le 0 \tag{6}$$

$$(c_y-e_y)(a_x-c_x)-(c_x-e_x)(a_y-c_y)\cdot$$
$$(c_y-e_y)(b_x-c_x)-(c_x-e_x)(b_y-c_y) \le 0 \tag{7}$$

(c) On a graph, calculate the shortest path between the first position and the goal position. In Fig. 3, compare route $A \rightarrow C \rightarrow D \rightarrow B$ and route $A \rightarrow E \rightarrow F \rightarrow B$. To work out the shortest path on graph, Dijkstra method are generally used.

These proceedings are added to particle filter algorythm. Fig. 4 is the flowchart of designed filter algorythm.

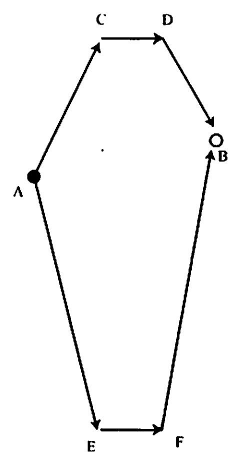

Fig. 3. An example applying the visibility graph algorytms

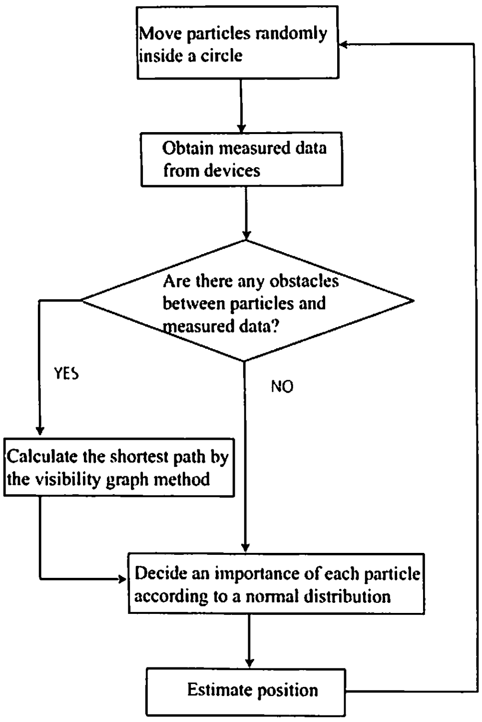

Fig. 4. Flowchart of designed filter

III. Experiments

To evaluate performance of the designed filter, experiments are conducted.

A. Experimental settings

We used a wireless-LAN location awareness system (Air Location II; Hitachi wirelessinfo venture company.). Aspect was shown in Fig. 5. Below are some features. This system measures the position using time difference of arrival (TDOA). This system can identify devices if a MAC address is registered in advance and find plural devices at once. It means that we can obtain location data and identify a person's data at the same time.

Experiments were performed in a large room: a hall at The University of Tokyo. The hall has partitions and can be divided. Therefore, we can simulate the presumed situation. Floor space is 21 m by 18 m. Then we set the measurement area 20 m by 16 m rectangle and placed Air Location II devices on each corner. We divided the hall into block A and block B. Blocks A and B were partly partitioned by a metallic wall.

B. A mode of experiment

We specifically examined places around the partition because these place are apt to have mistakes which block a

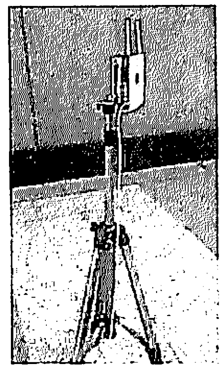

Fig. 5. Aspect of Air location II

person. Therefore, we walked the route shown in Fig. 6 four times. A device to send radio waves used an active tag (Air Location II). The tag also has a MAC address and sends a ping regularly. The system can change measurement cycles to some degree. We decided on a measurement cycle of four times per second, we obtain data every 0.25 secounds.

C. Simulation to determine the number of particles

Before doing experiments, the number of particles must be determined. Therefore, we simulated filtering as a change the number of particles. As in the simulation performed, noise follows a normal distribution which average is 0[m] and standerd deviation is 1[m]. Results are presented in Table II. The accuracy rate is the rate of whether the estimated position and real position are in the same block.

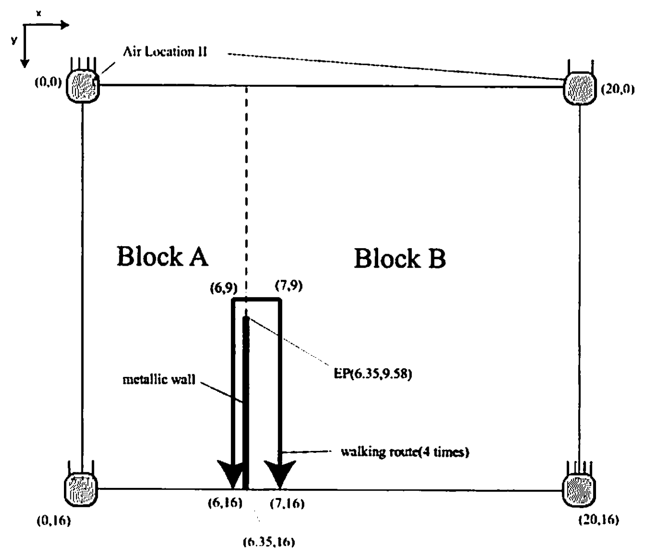

Fig. 6. Sketch of a hall and a walking route

TABLE II
DETERMINE THE NUMBER OF PARTICLES

number of particles	average error [m]	improvement percentage [%]	accuracy rate [%]	calculation time per data[sec]
(Without filter)	2.58	0	69.85	N/A
10	2.87	-10.89	73.67	0.0064
50	1.14	55.94	88.82	0.0264
100	1.10	57.39	88.19	0.0531
500	1.50	42.10	83.44	0.2531
1000	1.58	39.05	81.24	0.5113

TABLE III
AVERAGE ERROR AND IMPROVEMENT PERCENTAGE IN THE EXPERIMENT

average error without filter [m]	average error with filter [m]	improvement percentage [%]
2.603	2.030	22

TABLE IV
ACCURACY RATE IN EXPERIMENT

accuracy rate without filter [%]	accuracy rate with filter [%]
75.91	83.07

The improvement percentage I_p was defined as (8), where D is the average error without a filter and D_f is the average error after filtering.

$$I_p = (1 - D_f/D) \cdot 100 \quad (8)$$

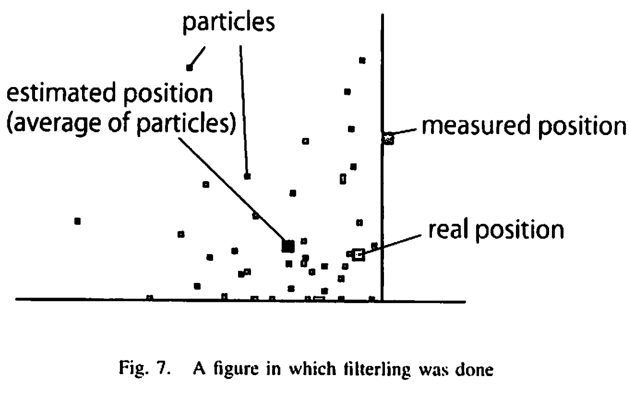

Fig. 7. A figure in which filterling was done

The results show that there are not such great differences in the improvement percentage and the accuracy rate between50, 100, 500 and 1000, which might imply that saturation occurs. On the other hand, the calculation time increases in direct proportion to the number of particles. Above and beyond 500, the calculation time becomes greater than the measurement interval 0.25[s]. It means filtering can not be done untill next position data is gotton, and filter can not be used in a real time situation. 50 is not enough to implove average error. Therefore, we decided to set the number of particles to 100.

D. Experimental results

Figure 6 presents the situation in which filtering was done. Particles are seen to estimate the block correctly, even measured position is the other side of the wall. Table III shows the average error and improvement percentage in experiment. Table IV shows the accuracy rate in the experiment.

Now we disscus our experiment. We are concerned that the average error and improvement percentage are less accurate than the results of simulation. Some reasons are inferred. First, although we presumed that the noise follows a normal distribution, the possibility exists that hypothesis is wrong. Second, the metallic partition biased by radio waves to the far side from the partition, as presented in Fig. 8.

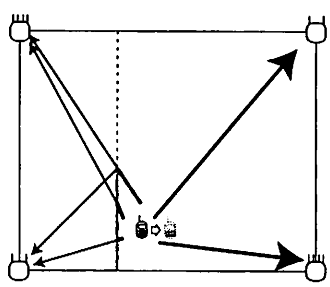

Fig. 8. Metallic partition makes reflection and diffraction of radio wave

TABLE V
THE ACCURACY RATE DIVIDED INTO DISTANCE FROM EP

distance from EP[m]	accuracy rate without filter [%]	accuracy rate with filter [%]
0.42 - 1.42	72.05	71.65
1.42 - 2.42	74.02	74.80
2.42 - 3.42	76.36	81.40
3.42 - 4.42	91.24	95.62
4.42 - 5.42	76.95	98.44
5.42 - 6.42	79.13	100.0

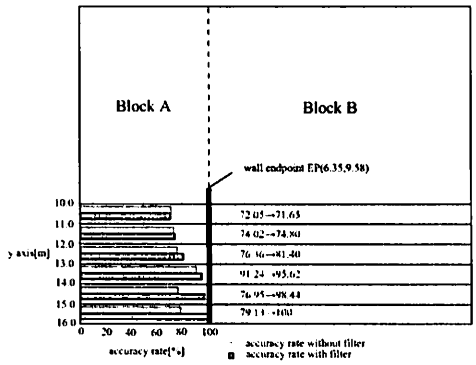

Fig. 9. Figure and graph of accuracy rate

Therefore, we considered the accuracy rate. Strictly speaking, 80% is insufficient for practical use. However, a good result is in prospect when designed filter is used in daily life such as shopping mall or department store. Table V and Fig. 9 presents the accuracy rate, which divides the distance from the wall endpoint EP $(x, y) = (6.35, 9.58)$. This table shows that the filter has strong effects as separate from EP. Consequently, the filter can be said to be sufficiently effective, except at the boundary.

IV. CONCLUSION

The results of this study suggest effective way to improve the estimated position by wireless sensors using the designed filter. Furthermore, we demonstrated that the designed filter is effective. Although several problems such as noise models and correctness around the boundary remain, the designed filter can be of practical benefit.

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