A Speed-Adaptive Location Estimator for Wireless LAN-based RTLS Systems

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Abstract

In this paper, we propose a location estimation algorithm which improves the positioning accuracy in wireless LAN-based real-time locating systems (RTLS) [1]*. For location estimation, the proposed algorithm makes use of the received signal strength (RSS) information and the speed information of mobile devices as well. We show that the proposed algorithm can provide better estimation accuracy than conventional ones through experiments, especially in positioning moving mobile devices.*

1. Introduction

As wireless LAN infrastructures are installed in many places and the needs for location-based applications emerge in many industrial areas, it becomes more important to develop accurate location positioning systems using wireless LAN technologies.

Wireless LAN-based location positioning systems are usually used indoor or in limited spaces such as manufacturing lines, large shopping malls, healthcare centers, amusement parks, or parking lots. In such environments, however, radio signals fluctuate significantly due to reflection, refraction, multipath, and so on, causing deterioration in estimating the true position of the located mobile device. Hence, ensuring high positioning accuracy is the most important and crucial issue in wireless LAN-based real-time locating systems (RTLS).

Off-the-shelf wireless LAN-based RTLS systems usually estimate the true position of mobile devices with accuracy of less than 3 meters when it is not moved [1]-[3]. Some RTLS systems provide 1-meter accuracy for stationary devices using a radio-signal map called fingerprint [4]. However, if the mobile devices tracked come to move, the estimation accuracy deteriorates and the error range extends up to 10 meters or more. Actually, in many cases, these large values are meaningless in local or indoor location positioning systems. Thus, it is indispensable to ensure high positioning accuracy irrespective of the moving speeds of located objects.

The location estimation algorithm proposed in this paper addresses this point. That is, the proposed algorithm makes use of both the received signal strength (RSS) information and the speed information to estimate the true position of mobile devices accurately. According to the speed of the located mobile device, the proposed algorithm varies the sampling rate at which the mobile device measures and transmits the RSS information to the location computation server. In this way, we can improve the accuracy of location estimation, when mobile devices are on the move.

This paper is organized as follows: In Section 2, we review location-estimation methods and location-display methods for wireless LAN-based RTLS systems. We also discuss the limitations in the existing location-display methods. In Section 3, we introduce an approach for overcoming the limitation of the existing location display methods. In Section 4, we perform several experiments and show the superiority of the proposed method. Finally, we conclude this paper with a brief summary in Section 5.

2. Location Estimation and Display Methods

Location positioning systems are composed of subsystems for location sensing, positioning engine, and display as shown in Fig. 1. In this section, we review the location estimation methods and the location display methods used in most location positioning systems.

2.1 Location Estimation Methods

Location estimation methods used in location positioning systems include Cell-ID, triangulation, and fingerprinting [6]-[7]. Among these, the Cell-ID scheme estimates

[1] Part of this paper will be presented in Korean at Telecommunications Reviews, vol.16, no.4, 2006.

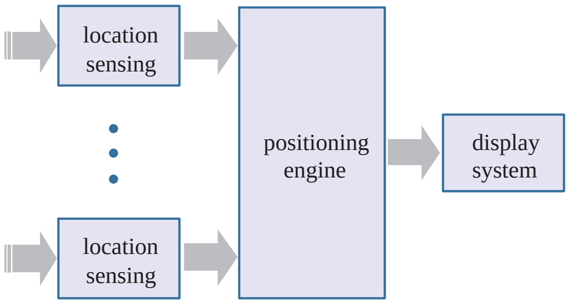

Figure 1. Functional block diagram of wireless location positioning systems [5].

the position of objects by identifying the cell where the strongest signal has been received from the located object. The Cell-ID scheme is a very simple approach in itself and thus employed in mobile communications systems and RFID-based RTLS systems. In mobile communications systems, however, since the cell size reaches up to 1 or 2 kilometers, it is preferable to check the object's existence/present in the cell rather than accurate location estimation. In RFID-based RTLS systems, on the other hand, the accurate location estimation is possible due to its small cell size (normally, couples of meters).

Location estimation by triangulation or trilateration calculates current position by acquiring the distances between the located mobile device and three reference points. The distances between the located device and reference points are obtained from the radio-wave metrics such as the received signal strength (RSS), time of arrival (TOA), and time difference of arrival (TDOA) [6]. Triangulation is usually adopted in the global positioning systems (GPS) and wireless LAN-based RTLS systems. GPS systems provide location estimation error which ranges from about 10 to 30 meters in horizontal and vertical estimations [8]. Wireless LAN-based RTLS systems estimate the true position with 10-meter accuracy for moving mobile devices.

Fingerprinting scheme uses radio environment information in addition to the radio metrics such as RSS and/or TOA in estimating the current location of mobile devices [9]. For example, it also considers the effect of diverse environmental factors such as the material of wall, number of walls, existence of furniture or machineries, open and close status of doors and windows, moving human body, number of people, and so on. Therefore, it is known that the fingerprinting scheme can provide most accurate location estimation among the three location estimation schemes. In the wireless LAN-based RTLS systems using fingerprinting, it is reported that the location estimation error is around 1 meter for stationary devices. Even though fingerprinting provides better estimation result than other schemes, this approach entails operational and managemental burdens since it has to update the radio-signal map whenever there occur any changes in radio environment.

2.2 Location Display Methods

Most location positioning systems estimate the current location of mobile devices by using one of the location estimation methods described in the previous subsection. (Some systems use two or more methods at the same time to improve the location estimation accuracy.) This estimation is performed for momentary location samples measured in a pre-fixed periodic interval. Considering, however, the fact that the signal level fluctuates abruptly in real situation as shown in Fig. 2, the location estimation result of a specific instant could be far from the true position of the located mobile device. For this reason, most location positioning systems calculate an average value for a specific duration of time as an estimated position, instead of presenting momentary location estimation results. (Here, let's call this specific duration of time 'an observation interval'.)

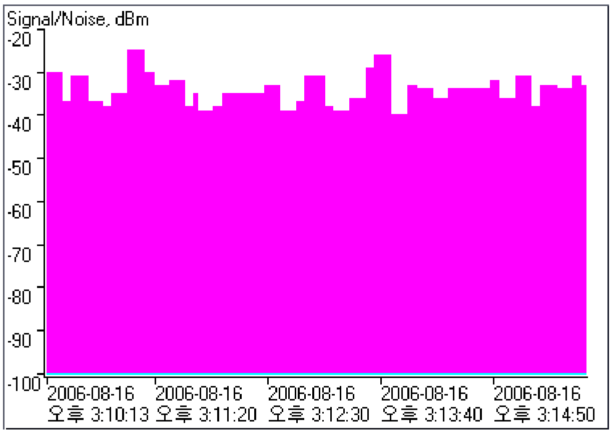

Figure 2. Signal to Noise ratio (dBm) of a stationary access point during 5 minutes, measured by NetStumbler [10].

Taking an average over samples measured during an observation interval, however, can be another factor causing location estimation error because it uses the past information in estimating the current position. In order to solve this kind of problem, we have to shorten the observation interval as short as possible or give weight to recent samples as much as possible. However, shortening the observation interval decreases the number of location information samples used in taking an average and may cause inaccuracy in estimating the true position. Giving weight to recent samples, on the other hand, may let the estimator be affected by unusually-exorbitant sample values. To keep the accuracy level of estimation, therefore, we have to maintain the number of samples used in the average calculation as constant as possible irrespective of the length of the observation interval. This is the main idea behind the location estimation algorithm proposed in this paper.

3 Speed-Adaptive Approach to Improve the Positioning Accuracy

As mentioned in Section 2, the location estimation function is performed by taking an average for the momentary location estimation results in an observation interval. This approach, however, may bring different estimation results depending on the length of the observation interval and the number of location information samples therein. This phenomenon gets worse either when the stopped object is about to move or when the object moves fast, which is the motivation of this study.

In this paper, therefore, we propose a location estimation algorithm which improves the positioning accuracy by adjusting dynamically the observation interval and the number of samples used in location estimation based on the moving speed of the object. Particularly, the proposed approach ensures the estimation accuracy irrespective of the moving speed of the mobile device by maintaining the number of location samples constantly.

The proposed approach consists of three parts: speed estimation of the moving object, control of the transmission interval of the location information based on the moving speed of the located object, and location estimation based on the location information transmitted. Here in this paper, we confine our interest to the first two components since the last component has been mentioned previously and dealt with in many other studies.

3.1 Estimation of the Moving Speed

The moving speed of mobile devices is calculated with the distance moved during a specific time interval (i.e., an observation interval) and the distance is obtained by summing unit distances δ_t for $t > 0$. Let (x_t, y_t) and (x_{t-1}, y_{t-1}) represent the estimated location coordinates of the current and previous unit time tick, respectively. Then, the unit distance δ_t between the two coordinates is

$$\delta_t = \left((x_t - x_{t-1})^2 + (y_t - y_{t-1})^2 \right)^{1/2} \text{ for } t > 0 \quad (1)$$

and the distance moved for a specific time interval d_i becomes

$$d_i = \sum_{j=1}^{t} \delta_j. \quad (2)$$

However, Eq. (2) can not be used in itself since the estimated location (x_t, y_t) could be different from the real location due to the uncertainty of the radio environment. For all that, we also can not use Eq. (1) for the start and end points of the observation interval, instead of Eq. (2). If we do, the distance where the located object moves during the observation interval could be shorter than the distance where the object moves actually in cases that it turns its direction. Therefore, if we could know the turning point where the moving object changes its direction, we can express the distance moved during the observation interval d_j as follows:

$$d_i = d\left(l_s, l_{t(0)}\right) + \sum_{j=1}^{t} d\left(l_{t(j)}, l_{t(j-1)}\right) + d\left(l_e, l_{t(k)}\right). \quad (3)$$

where l_s and l_e indicate the start and end points of the observation interval respectively and $l_{t(j)}$ $(1 \le j \le k$ and $1 \le k)$ indicate the turning points between the start point l_s and the end point l_e.

Now, the matter of estimating the moving speed becomes the matter of finding out the turning points during the observation interval. However, it is not easy to find turning points, even though we may be able to find them via a complicated direction estimation process. In this paper, therefore, we assume that mobile devices carry out a rectilinear movement during the observation interval since the interval might be very short in reality.

3.2 Adjustment of the Sampling Interval of the Location Information

In terms of the moving speed, the status of the located object can be either stationary or moving. When the located device is in the moving status, the status can be further divided into constant, monotonic increase, and monotonic decrease in terms of the speed. In reality, however, transient periods are very short and thus objects are mostly either in the stationary status or in the constantly-moving status. Therefore, if we assume that the transient periods are very short enough to be neglected, the issue of the sampling interval adjustment of the location information becomes very simple. That is, we will consider only two statuses: stationary and moving.

When mobile devices are moving, the moving speed can be divided into several speed ranges. For example, let's assume that an RTLS system measures the received signal strength once in a second. And further assume that the travelling speed of the traced object is 18 Km/hr (or 5.0 m/sec) [2]. Since the wireless LAN-based RTLS systems can measure location information 8 times a second generally, we

[2]The speed of 18 Km/hr corresponds to the traveling speed of the forklift in the industrial area. Human walks at the speed of 3.2 Km/hr or 0.9 m/sec.

measure 8 times when the located object moves at its maximum speed and divide the speed into 4 speed ranges as shown in Table 1. Then, the number of samples for a unit interval stays constant irrespective of the speed range.

Table 1. Example: Number of samples used for different speed intervals.

speed interval (m/sec)	0.00-0.63	0.63-1.25	1.25-2.50	2.50-5.00
unit interval (sec)	4.0	2.0	1.0	0.5
samples	1	2	4	8
no. of samples per unit interval	4	4	4	4

In order to maintain the number of samples constant, we need to know the speed of mobile devices. The speed v during an observation interval can be calculated as follows:

$$v = \frac{d_i}{k \cdot \Delta t}$$

where k and Δt denotge the number of samples during the observation interval and the duration of the unit interval, respectively. For d_i, we may use the expression in Eq. (3) or in Eq. (2).

According to the approach proposed in this paper, consequently, the functional block diagram of the wireless LAN-based location positioning system in Fig. 1 is expressed as shown in Fig. 3.

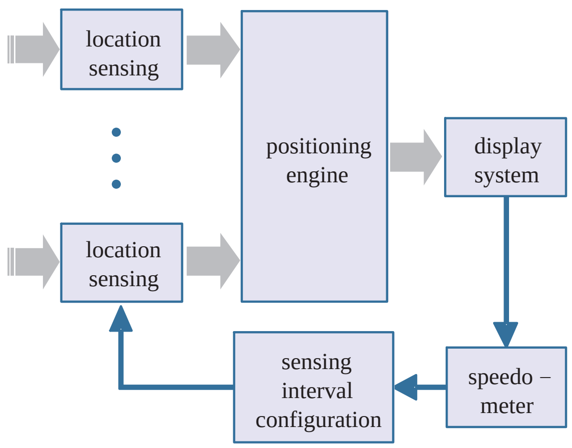

Figure 3. Functional block diagram of the speed-adaptive location estimator proposed in this paper.

4 Performance Evaluation

In this section, we validate that the speed-adaptive approach introduced in Section 3 provides better location estimation accuracy than conventional methods through performance tests. In the test, we used the wireless LAN-based RTLS system of AeroScout Inc. [1]. The role of the AeroScout RTLS system in the test was to provide real-time measured data which was used to obtain estimated data by the proposed algorithm and the conventional methods.

Figure 4. Test environment.

For the test, we deployed 4 wireless LAN APs (AeroScout's Location Receivers) in the 8th floor of the ASEM Tower in Seoul, S. Korea as shown in Fig. 4. All the APs support only the IEEE 802.11b standard and use an omni-directional antenna (15 dBm). As mentioned in the previous section, we assumed that mobile devices do a rectilinear movement in the observation interval. As the mobile object, we used a notebook (Samsung SENS P20) and a PDA (HP iPAQ HX2490) as shown in Fig. 4.

Table 2 shows the comparison result when the mobile devices are placed in an aisle in the middle of the office space as shown in Fig. 4. In this case, there is no much difference among three approaches as shown in Table 2: speed-adaptive approach, mean, and median. Especially, the estimation results for the approaches using speed adaptation and mean are same to each other. It is because the proposed approach is based on the mean calculation in determining the location irrespective of the speed of the located object. In this experiment, we used 2,400 samples for each device during 10 minutes and used samples measured recent 5 seconds (i.e., the observation interval is 5 seconds) in taking an average.

Table 2. Comparison of the estimation accuracy among three approaches when the located object is stopped.

Accuracy	Proposed	Mean	Median
1 m	39%	39%	36%
2 m	40%	40%	41%
3 m	15%	15%	20%
4 m	5%	5%	3%
5 m	1%	1%	0%
6 m	0%	0%	0%
Avg.	1.89m	1.89m	1.9m

Table 3. Comparison of the estimation accuracy among three approaches when the located object is moving at the speed of 0.9 m/sec.

Accuracy	Proposed	Mean	Median
1 m	11%	3%	3%
2 m	16%	8%	7%
3 m	25%	10%	9%
4 m	27%	17%	16%
5 m	15%	19%	20%
6 m	5%	18%	22%
7 m	1%	11%	17%
8 m	0%	7%	5%
9 m	0%	3%	1%
10 m	0%	0%	0%
Avg.	3.38m	4.80m	5.07m

On the contrary, our experiment on the estimation accuracy of the moving object shows completely different results. As shown in Table 3, the speed-adaptive approach, proposed in this paper, yields much better estimation accuracy than other approaches using mean or median when the located object is assumed to be moving at 0.9 m/sec. With the proposed approach, we could get more accurate estimation results than others by around 1.5 meters as shown in Table 3 and Fig. 5. As shown in Fig. 5, the proposed algorithm provides 5-meter estimation accuracy with the possibility of 90 percent. In this experiment, the sampling rate was chosen to be 4 samples/sec for approaches using mean or median and 8 samples/sec for the proposed approach.

5 Conclusions

As the needs for wireless LAN infrastructures and location-based applications increase, various wireless

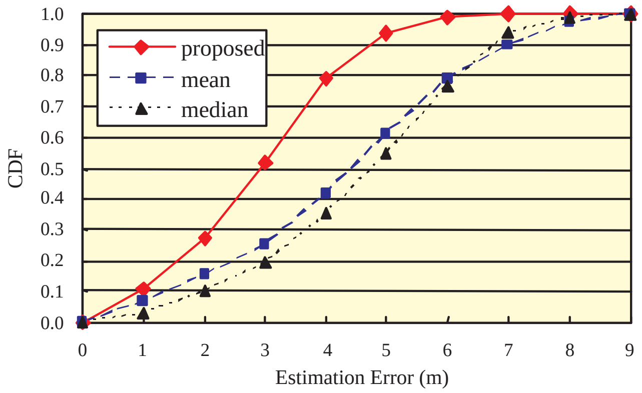

Figure 5. Cumulative Distribution Function (CDF) of the estimation error for three location estimation approaches.

LAN-based location positioning systems have been developed and introduced. These systems are mostly used in an indoor area such as manufacturing lines or in specific local areas such as parking lots or amusement parks. In indoor environment, however, location positioning accuracy as well as the quality of data communication are subject to the fluctuation of radio signal. Therefore, keeping the location positioning accuracy high enough is one of the most crucial issues that must be vanquished.

In this paper, we introduced a method to improve the location positioning accuracy in the wireless LAN-based RTLS system. In the proposed approach, we harness the speed information of mobile devices as well as the location information in order to estimate the position real-time. That is, after estimating the speed of mobile devices, the interval of sampling location information is varied according to the moving speed. By doing so, we can improve the location estimation accuracy by 1.5 meters when the object is moving at a human-walking speed. Even though we could improve the location estimation accuracy with the proposed algorithm, its effect is limited. It is because that the proposed algorithm tries to use as recent location information as possible, instead of reflecting the real-time changes in radio environment. The effect of a changing radio environment will be considered in our next study.

References

[1] AeroScout Inc., http://www.aeroscout.com

[2] PanGo Networks Inc., http://www.pangonetworks.com

[3] Wherenet Inc., http://www.wherenet.com

[4] Ekahau, http://www.ekahau.net

[5] K. Pahlavan, X. Li, and J.-P. Makela, "Indoor Geolocation Science and Technology," *IEEE Communications Magazine*, vol. 40, no. 2, pp. 112-118, Feb. 2002.

[6] K. Kolodziej and J. Danado, "In-Building Positioning: Modeling Location for Indoor World," *Proc. of the 15th Int'l Workshop on Database and Expert Systems Applications*, pp. 830-834, Sept. 2004.

[7] S. Ito and N. Kawaguchi, "Bayesian Based Location Esti-mation System Using Wireless LAN," *Proc. of the 3rd Int'l Conf. on Pervasive Computing and Communications Workshops (PerCom 2005)*, pp. 273-278, March 2005.

[8] P. Enge and P. Misra, "Special Issue on Global Positioning System," *Proceedings of the IEEE*, vol. 87, no. 1, pp. 3-15, Jan. 1999.

[9] A. Taheri, A. Singh, and E. Agu, "Location Fingerprinting on Infrastructure 802.11 Wireless Local Area Networks (WLANs) using Locus," *The 29th Annual IEEE Int'l Conf. on Local Computer Networks*, pp. 676-683, Nov. 2004.

[10] NetStumbler 0.4.0, http://www.netstumbler.com