Journal of Information Processing Vol.20 No.3 749–756 (July 2012)

[DOI: 10.2197/ipsjjip.20.749]

Regular Paper

An Integration Method for Wireless Location Using Built-in Sensors of Mobile Phones and TDOA Landmarks

Mingmei Li[1,a) Naoki Imai[2] Kiyohito Yoshihara[1]

Received: September 30, 2011, Accepted: April 2, 2012

Abstract: Non-line-of-sight (NLOS) signal propagation is the major source of error in wireless Time Difference of Arrival (TDOA) indoor systems. Even if enough landmarks (LMs) can be deployed by the service providers or system designers, the existing methods experience the location accuracy problem when few line-of-sight (LOS) measurements can be detected. Under the condition that the total number of TDOA measurements satisfies the minimum triangulation requirements (≥ 3), this paper proposes a new integrated location method. The proposed method integrates the user's step length and count from the built-in sensors of mobile phone into the wireless TDOA location systems. Firstly, it detects LOS/NLOS measurements using the user's step length and count. Secondly, it integrates the previous location and step length as supplementary LM and measurement to estimate the location, when two LOS measurements are detected. Simulation results show that the proposed method detects LOS/NLOS measurements at a higher ratio. Performance of location errors depends on the number of detected LOS measurements. The proposed method achieves lower location errors when two LOS measurements are detected.

Keywords: built-in sensors of mobile phones, TDOA landmarks

1. Introduction

Recently, mobile devices are wide spread. The location information of mobile devices is expected to be used in many new services, such as friend finding, shopping guides, etc. While many mobile phones have GPS receivers, some services should be provided in situations where the function of GPS receivers is not available, such as indoor areas, underground areas and complicated urban districts with a lot of buildings.

Many studies have investigated wireless location technologies and some services are available today [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. The TDOA wireless location system is one of the indoor location systems. The location system estimates the user's location by relying on the time propagation between a mobile device and landmarks. When the moving mobile device users meet obstacles, encounter multipath effects, NLOS errors occur, making the tracking accuracy worse. The presence of NLOS measurements is a serious issue in wireless location, because these errors tend to be very large and, hence, can dramatically degrade location accuracy [11], [12].

Mitigating NLOS measurements has attracted a lot of attention and several optimization algorithms have been proposed [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21]. Broadly speaking, the literature on the NLOS problem falls under two categories: NLOS identification [13], [14] and NLOS mitigation [15], [16], [17], [18], [19], [20], [21]. The former deals with the problem of distinguishing between LOS and NLOS range information, whereas the latter typically deals with the reduction of the adverse impact of NLOS range errors on the accuracy of location estimates, assuming that the NLOS range estimates have been identified. To mitigate the NLOS errors, a biased Kalman filter algorithm is proposed in Ref. [11]. The existence of the NLOS component is identified first. The range measurements are smoothed for calculating the standard deviation in a hypothesis testing. This biased Kalman filter algorithm avoids inaccurate estimation of the range rate from the NLOS mitigation. However, it may result in large error interpreting NLOS conditions into LOS ones. The noise covariance generated by an NLOS error is compensated only when the measured range data is smaller than the estimated range data. Several statistical NLOS-identification techniques [12], [13], [14], [15], [16], [17], [18], [19], [20], [21] for TDOA/ time of arrival (TOA) systems have been discussed previously, which exploit prior knowledge of NLOS delays and a series of measurements to reduce the bias in NLOS range estimates. NLOS detection measurements results indicate that when the square residual between the estimated distance and the measured distance cannot be updated on time, usually overestimate or underestimate of the measurement happens. Mobile phone with built-in sensors is well-suited to solve the problem due to its support of diverse sensors which enable localization (e.g., 3axis, magnetic, gyro, etc.). In this sense, recent research works [7], [8], [9], [10] presents location-based services running on carried sensors or mobile phone built-in sensors based largely on outdoor GPS use, but precise indoor localization would require complicit computation cost on a mobile phone.

[1] KDDI R&D Laboratories, Inc., Fujimino, Saitama 356–8502, Japan
[2] KDDI CORPORATION, Chiyoda, Tokyo 102–8460, Japan
[a)] mi-li@kddilabs.jp

With the condition that the total number of TDOA measurements satisfies the minimum triangulation requirements ($\geq$ 3), this paper proposes a new integrated location method. The proposed method integrates the user's step length and count from the built-in sensors of mobile phone into wireless TDOA indoor location systems. Firstly, it detects LOS/NLOS measurements using the user's step length and count. Secondly, it integrates the previous location and step length as supplementary LM and measurement to estimate the location, when two LOS measurements are detected.

For the proposed method, location estimation is based mainly on TDOA distance measurements (at least three TDOA measurements); user's step-length and count (mobile phone built-in sensor information) are added in our method when few TDOA distance measurements are accurately received (LOS measurements = 2). For The Pedestrian Dead Reckoning (PDR) System, location estimation is mainly based on the user's step-length, counts and direction estimation (information from the built-in sensors of mobile phone).

The paper is organized as follows. Section 2 briefly describes the wireless TDOA location system. Section 3 presents the motivation for using the built-in sensors of mobile phone. Section 4 illustrates the details of the proposed method. Section 5 gives the simulation results comparing the proposed method with the existing method. Finally, Section 6 concludes the paper.

2. Wireless TDOA Location System

2.1 System Architecture

Figure 1 illustrates a wireless TDOA location system with several LMs and an MP user. The true distance r_i between the i_{th} LM at coordinate (x_i, y_i) and the MP at coordinate (x, y) can be described as,

$$r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{1}$$

2.2 NLOS Problems in the System

As shown in Fig. 1, an NLOS error results from the blockage of the direct measurement and the reflection of multipath measurements between LM2 and the MP. With receiver noise and NLOS errors, the measured distance r_i can be expressed as

$$d_i = r_i + n_i + NLOS_i \tag{2}$$

where n_i represents the receiver noise, and $\mathrm{NLOS_i}$ represents the NLOS error from the i_{th} LM. The receiver noise n_i is assumed to be a zero-mean Gaussian random variable. An NLOS error can be described as a deterministic error, a Gaussian error, or an exponentially distributed error [11], [12]. Since the measured distance in a TDOA location system is much larger than the receiver noise [11], [12], the location errors result mainly from the NLOS errors.

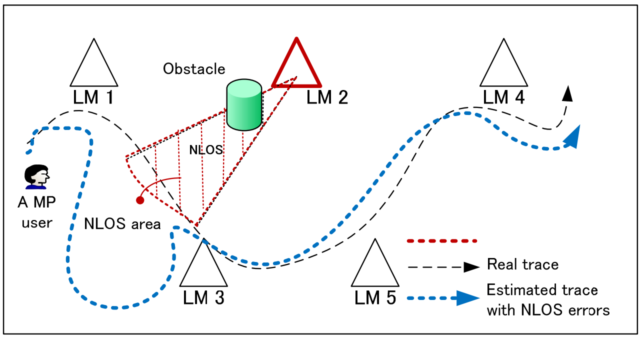


Fig. 1 NLOS problem in wireless TDOA indoor location system.

3. Built-in Sensors in Mobile Phone

3.1 Sensor Data from Mobile Phone

Manual configuration of locations is not feasible for large-scale networks or networks. Providing many sensors with localization hardware (e.g., GPS) is expensive in terms of cost and energy consumption [2]. A more reasonable solution to the localization problem is to allow mobile phones to have their step information at all times, and allow users to infer this information from these sensors [8], [10]. Recently, mobile phones with built-in sensors (e.g., 3-axis, magnetic, gyro sensors, etc.) have been wide spread. These sensors help provide a lot of a user's information that can be used in a location system: arm swing detection, step count estimation, direction estimation and step length estimation. In this paper, we use step count estimation with an error between −10% and +2% and step length estimation with an error between −10% and +9% [10].

3.2 Measurement Combination

For measurement combinations, TDOA measurements are obtained from LMs to estimate the position of a mobile phone. At least, four TDOA distance measurements from LMs are required to estimate the position of a mobile phone. If the number of TDOA measurements is less than four, mobile phone built-in sensor data is combined with TDOA measurements. In the next section, we propose a new method to yield satisfied location estimation when less LOS measurements are available. The basic idea is to integrate step length and counts from the built-in sensors of mobile phone into the wireless TDOA location system.

4. The Proposed Location Method

For wireless TDOA location, in mixed LOS/NLOS environments, as multiple TDOA measurements are collected, some of them may be biased by NLOS errors at a certain time step. If we could effectively detect those LOS measurements and make use of them to locate the MP, the performance of the classical location algorithms will be better than using a mixed set of LOS/NLOS measurements. Therefore, the proposed method falls in two steps: LOS/NLOS measurements detection and location estimation. As shown in **Fig. 2**, TDOA measurements and built-in sensor measurements are received as inputs for LOS/NLOS measurements detection, then detected LOS measurements are used to estimate the user location. The detailed steps of the

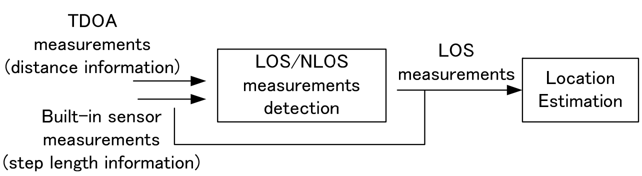


Fig. 2 The flowchart of the proposed method.

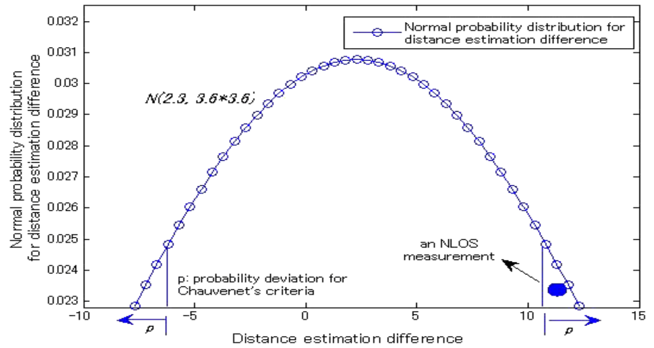


Fig. 3 An example of Chauvenet's criterion test.

LOS/NLOS measurement detection method and location estimation method are described in Sections 4.1 and 4.2 separately.

4.1 Part I: LOS/NLOS Measurements Detection

In the following, we focus on LOS/NLOS measurements detection. In this part, the physical statistical properties of a user's movement at the current time is treated as continuous data in a short time interval. In the previous square-residual related methods [13], [14], [15], [16], [17], [18], [19], [20], once the residual between the predicted and the measured distance value is larger than a threshold, the measured distance is detected as a NLOS measurement. However, the square residual between the estimated distance and the measured distance is usually overestimated or underestimated when the knowledge of user location estimation cannot be updated on time. The proposed method utilizes the user's step length and counts from mobile phone built-in sensors as the reference to help detect LOS/NLOS measurements.

In this part, at each time step, we firstly get an estimated position of the MP using the LS algorithm, using last position, step length and all TDOA measurements. Then we substitute the estimated position of the moving MP to the measurement Eq. (1) to obtain estimated distances for each hearable LM. And then, we form a normal distribution for the estimation differences. Finally, we use Chauvenet's criteria to separate LOS and NLOS measurements from this normal distribution. In statistical theory, Chauvenet's criterion is a method of assessing whether one piece of experimental data from a set of observations, is likely to be spurious [22], as shown in **Fig. 3**. Notice that, at the begining of the proposed method or when the MP is stantionary, the measurements of distances are repeatedly received from hearable LMs several times. The flowchart is shown in **Fig. 4**. The detail steps are described below.

[Step 1] Receive TDOA signals from LMS and estimate the initial location of an MP. We make use of the WLS (weighted least square estimation) method [19], to estimate the initial location of an MP. To reduce the computation cost, we use the LS method to estimate the location of the MP [12] in the following step.

[Step 2] Integrate step length and count from the built-in sensors of mobile phone. It can be achieved by Refs. [8], [10].

[Step 3] Generate an estimated location using last location of the MP, step length, and all hearable TDOA measurements with the LS method; if the current location is not an initial location.

[Step 4] Generate the estimated distance by substituting the estimated position (step 3) of the moving MP to the measurement

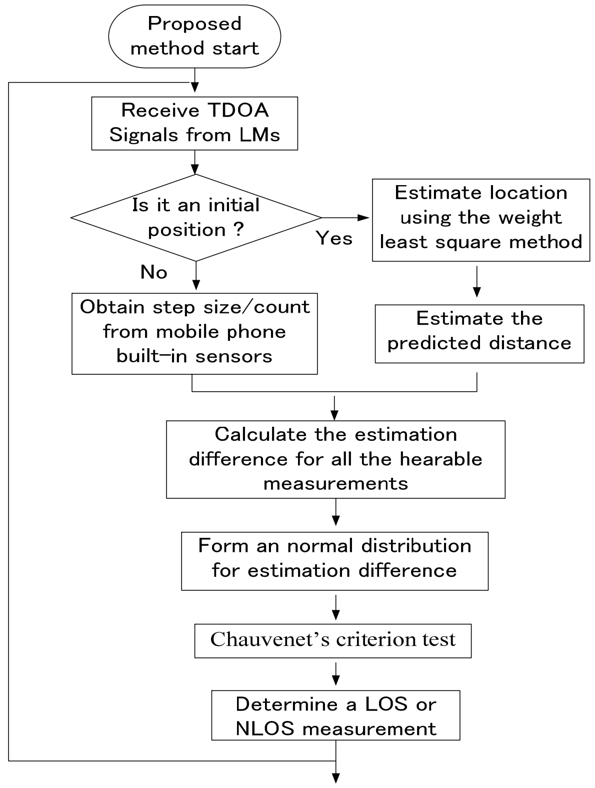


Fig. 4 The flowchart of LOS/NLOS measurements detection.

Eq. (1) to obtain estimated distances for each hearable LM.

[Step 5] Generate estimation differences for the distance measurements from all hearable LMs.

$$\gamma_i(k) = d_i(k) - H_i(k) \tag{3}$$

$\gamma_i(k)$ is the estimation difference, $d_i(k)$ is the measured distance and $H_i(k)$ is the estimated distance from the i_{th} LM at time point k, computed from step 4. $\gamma(k) = (\gamma_1(k), \gamma_2(k), \ldots, \gamma_N(k))$

[Step 6] Generate a normal distribution for $\gamma(k)$; and calculate the probability deviation for $\gamma_i(k)$.

[Step 7] Calculates Chauvenet's criterion test [20] for the generated distribution;

$$C(\gamma_i(k)) = P(\gamma_i(k)), \sim N(\bar{\gamma}(k), \sigma^2(k))) * (n * p) \tag{4}$$

where $C(\gamma_i(k))$ represents the Chauvenet's criterion test result for the estimation set $\gamma(k)$. p is the number of LOS measurements in $\gamma(k)$.

[Step 8] Determines the current measurement is an LOS or an NLOS one. Equations (5), (6) illustrate the determination rules. If the test results show that the current measurement is a LOS measured distance, we add it to the LOS measurements to form a new estimation distribution.

$$\text{LOS measurement} \quad C(\gamma_i(k)) < 0.5 \tag{5}$$

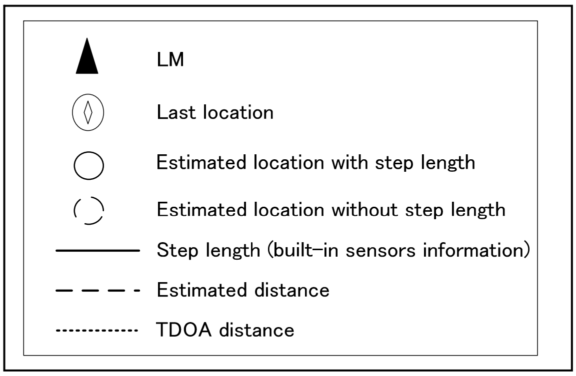
$$\text{NLOS measurement} \quad C(\gamma_i(k)) \geq 0.5 \tag{6}$$

Figure 5 shows an example for the proposed LOS/NLOS detection method. Assume that the measured distances from LM1 to LM4 is $(18.1, 6.3, 12.6, 14.6)$; step length is 7.6 m in five seconds, then the estimated distance from LM1 to LM4 is calculated as $(9, 8.4, 10.2, 15.8)$. The estimation difference is

Journal of Information Processing Vol.20 No.3 749–756 (July 2012)

$(9.1, -2.1, 2.4, -1.2)$. The normal distribution of a user's step length can be obtained as $N(2, 3.5^2)$. Finally, the result for Chauvenet's criterion test is that, the measured distance from LM1 (18.1) is regarded as an NLOS measurement.

Table 1 Summary of the labels.



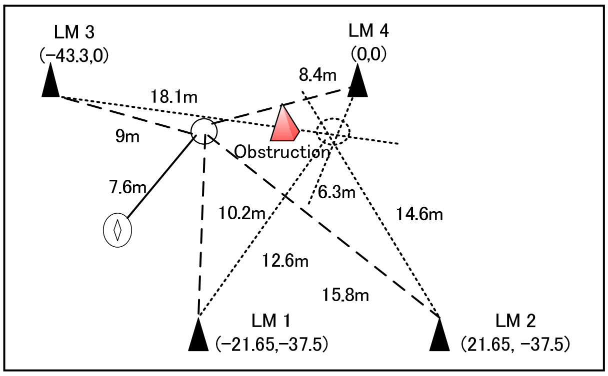


Fig. 5 The flowchart of LOS/NLOS measurements detection.

4.2 Part II: Location Estimation

In mixed LOS/NLOS environments, the estimated location of the MP from all measurements may be far away from the true location due to the NLOS problem. As multiple TDOA measurements are collected, some of them may be biased by NLOS error at a certain time step. If we could effectively detect those LOS measurements and make use of them to locate the MP, the performance of the classical location algorithms will be better than using all mixed LOS/NLOS measurements. However, if the number of hearable LOS measurements is few, it will be a problem to estimate the location of MP. In this subsection, the idea of the proposed method is for the LS algorithm to estimate the location of an MP directly; if the number of hearable LOS measurements is two, we combine the last location of MP, the step length, and hearable NLOS measurements into the LS algorithm to estimate the location. The flowchart is shown in **Fig. 6**. The details steps are shown below.

[Step 1] Receive TDOA measurements from hearable LMs.

[Step 2] Check the number of LOS measurements. It can be achieved by Part I.

[Step 3] Integrate step length and count from the built-in sensors of mobile phone. The step length for the user is estimated as follows,

$$s_{length}(k) = s_{size}(k) * s_{count}(k) * (1 + \alpha\%) \tag{7}$$

s_{length} is the step length of the user;
s_{size} is the step size of the user per second;
s_{count} is the count of the user step;

[Step 4] Get all the combinations which contain N-1 TDOA location measurements and built-in sensor measurements. Form two

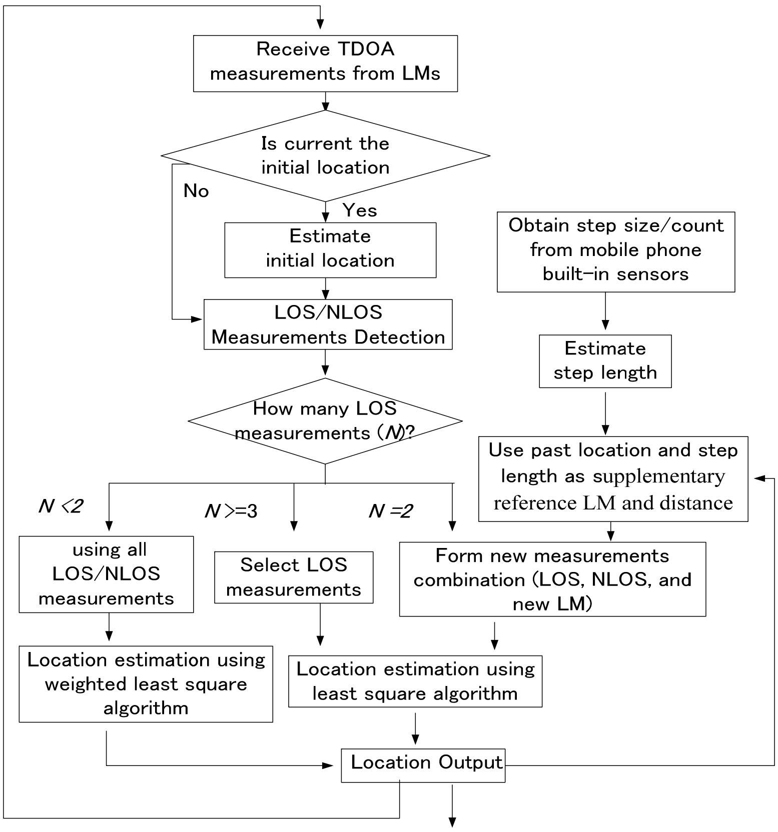
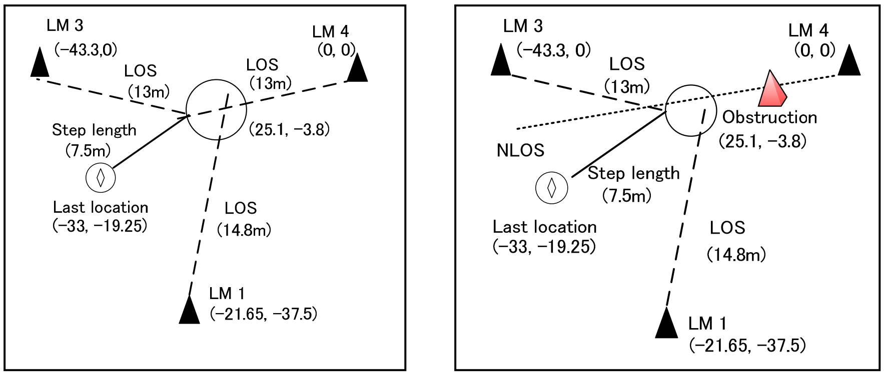


Fig. 6 The flowchart of location estimation.



(a) (Three LOS measurements) (b) (Two LOS and one NLOS measurements)

Fig. 7 An example of location estimation.

combinations,

$$N_1 = \sum_{i \in LMs}^{N_1} \binom{N_1}{i};$$

$$N_2 = \sum_{j \in LMs,\ sensors}^{N_2} \binom{N_2}{j};$$

N_1 is the set that only combines the measurements from the LMs; N_2 is the set that combines the measurements from the LMs and built-in sensors.

[Step 5] Estimate the user's location by using LOS measurement in combination N_1 with the LS algorithm, if the hearable LOS measurements are bigger than or equal to three.

[Step 6] Estimate the location by using the last location, step length, LOS and NLOS measurements, if hearable LOS measurements are two. The last position of the as distance measurements from $\mathrm{LM}_{\mathrm{past}}$.

[Step 7] Estimate the user's location by using all LOS/NLOS measurements in combination N_1 with the WLS algorithm, if the hearable LOS measurements are less than three.

Figure 7 (a), (b) shows an example for the proposed location estimation method. Figure 7 (a) is the scenario, where three TDOA signals are received; all these signals are detected as LOS measurements. Therefore, the location is estimated by using these three LOS measurements with the LS algorithm directly. The estimated location is $(25.1, -3.8)$. Figure 7 (b) depicts the scenario, where the three TDOA measurements are received and the signals from LM2 are detected as a NLOS measurement. Therefore the current location is estimated by using the two LOS measurements (13 m and 14.8 m) from LM1 $(0, 0)$, LM3 $(43.25, 0)$ and the last location $(12, -14.3)$; and the step length with 7.5 m. Then using LS method, the estimated location is $(24.3, -4.7)$.

5. Simulations

In this section, simulations are performed to evaluate the performance of the proposed method.

5.1 Simulation Setup

We consider a simulation scenario, where 7 LMs and an NLOS area with 4 obstructions are placed in the simulation area, as shown in **Fig. 8**. The coordinates of each LM are as:

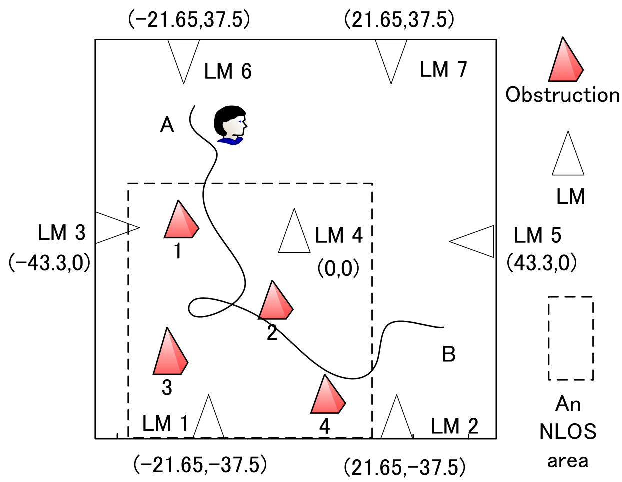


Fig. 8 Simulation scenario.

$(0, 0)$, $(-\sqrt{3}\mathrm{R}, 0)$, $(\sqrt{3}\mathrm{R}, 0)$, $(-\sqrt{3}\mathrm{R}/2, 3\mathrm{R}/2)$, $(\sqrt{3}\mathrm{R}/2, 3\mathrm{R}/2)$, $(-\sqrt{3}\mathrm{R}/2, -3\mathrm{R}/2)$, $(\sqrt{3}\mathrm{R}, -3\mathrm{R}/2)$. The transmission distance (R) of an LM is assumed to be 25 m. Hearable LMs are varied from four to six. Considering the impact of the wireless irregular radio distance, we assume that the radio distance of LM follows the Gaussian distribution $N(0, 0.5^2)$.

To evaluate the localization performance, the user is simulated to walk in a pre-determined route in the simulation area. As shown in Fig. 8, A is the start point and B is the end point of the user's walking trajectory. C is an NLOS area where some TDOA measurements are biased by obstructions. The user encounters NLOS1 at 30 s, NLOS2, 3 at 90 s and NLOS4 at 150 s in their walking trajectory. When the TDOA measurement from the i_{th} LM is simulated to be biased by an NLOS error, we added a distribution to the true measurement represent for an NLOS error. If we consider the NLOS error as a random variable, a simple way to model it is to use the Gaussian distribution with $mean_{\mathrm{nlos}}$ and $variance^2_{\mathrm{nlos}}$ [17]. For the purpose of simulation, the NLOS error is set as Gaussian distribution $N(0, 5^2)$. The unit used here is meter and it can be scaled to other units [18]. The number of NLOS measurements is varied according to the performance evaluation. We simulate a user's step length using built-in sensor data from mobile phones in Refs. [14], [15]. A random walking speed is selected between 0.8 m/s∼1.4 m/s for an adult user [17]. The user's walking distance is obtained at each second. The user's step size at each second is sampled from the walking distance with ±10% error [10]. All the simulation results are the average 50 runs.

5.2 Algorithms Compared

For part I: LOS/NLOS measurements detection, two methods are used for comparisons,

- KF: a Kalman filter-based mitigation algorithm [13]. The existence of the NLOS component is identified first. Then the distance measurements are smoothed for calculating the standard deviation using a hypothesis testing.
- RV: a distance variance-based estimation method introduced in Ref. [14]. It estimates the relevant parameters to certain thresholds, and then distinguishes NLOS measurements from LOS ones.

For part II location estimation, two methods are used for comparisons,

- LS: the method introduced in Ref. [12]. It uses range measurements to produce location estimation.
- WLS: the method introduced in Ref. [18]. The residual weight of each intermediate estimate is calculated first to generate location estimation.

For Part II: two ways of our proposed method are used for comparisons,

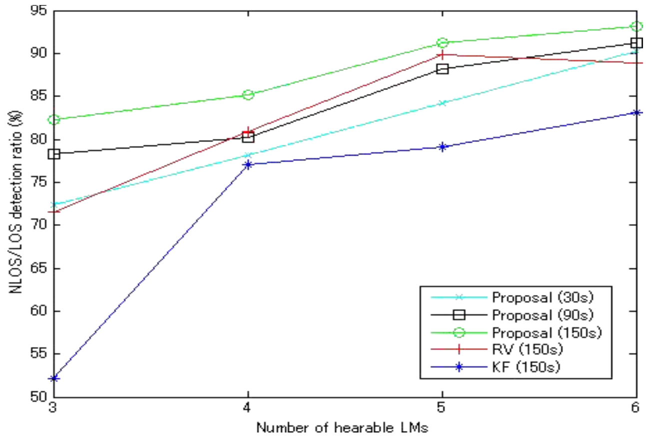
- LOS measurement only: the first evaluation of the proposed method. Detect LOS measurements by part I then use them with the LS methods to estimate the location.
- Combination: the second evaluation of the proposed method. This evaluation uses detected LOS measurements, last location and step length information with LS methods to estimate the location.

5.3 LOS/NLOS Measurements Detection

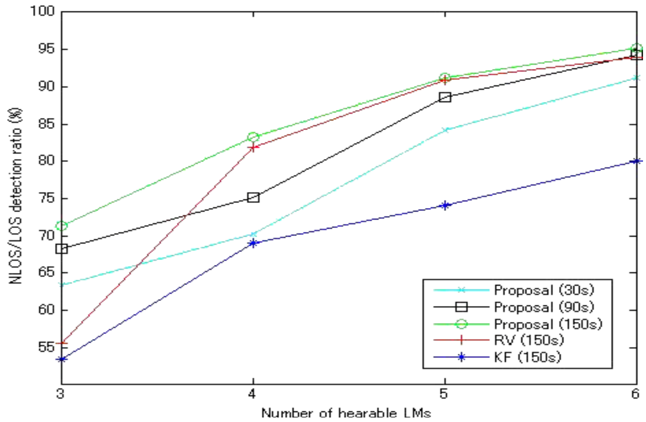
In this subsection, we want to make detailed observations and comparisons for the proposed LOS/NLOS measurements detection method. LOS/NLOS measurement detection ratio is used as an evaluation metric. In the evaluations, two conditions are considered to be wrong detection results: NLOS measurements detected as LOS measurements; and LOS measurements detected as NLOS measurements. Therefore, the LOS/NLOS measurement detection ratio is defined as,

$$(Measured_{\text{total}} - Measured_{\text{wrong}})/Measured_{\text{total}} * 100\% \quad (8)$$

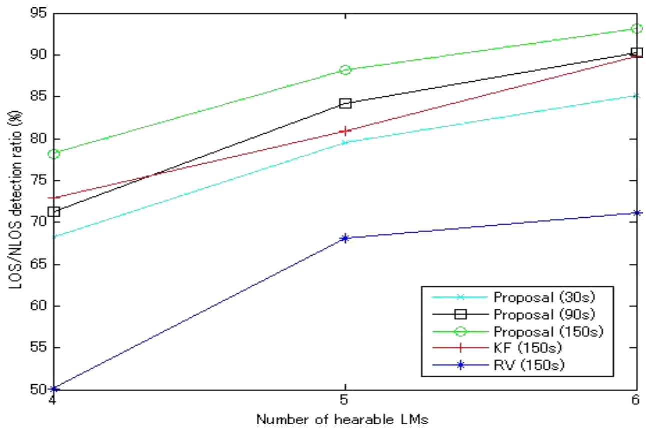
Where $Measured_{\text{total}}$ is the number of TDOA measurements that are detected totally and $Measured_{\text{wrong}}$ is the number of TDOA measurements that are detected wrongly. Larger detection ratio means better result. The simulation results are summarized in **Fig. 9** (a), (b), (c) for different combinations of LOS/NLOS measurements. Obviously, the KF method performs worst in all scenarios, attaining around 50–75% detection ratio. This is because using the bias Kalman filter method, NLOS errors will not be detected when the measured distance is bigger than the predicted distance. The bias adjusting rule makes the detection less effective since some NLOS measurements are easy to be identified as LOS measurements. The RV method performs well when four or five TDOA measurements are heard, as LOS/NLOS de-



(a) NLOS = 1



(b) NLOS = 2



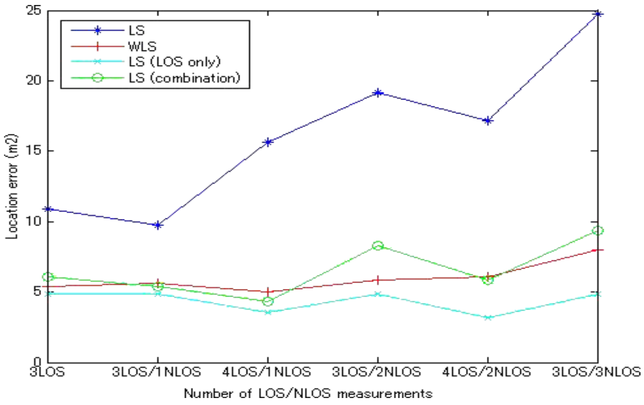
(c) NLOS = 3

Fig. 9 LOS/NLOS measurements detection ratio.

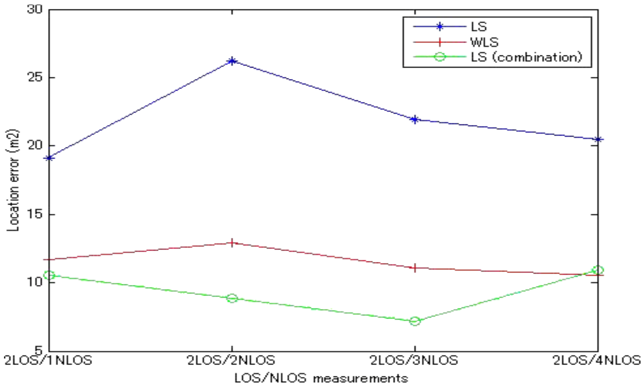
tection ratio is about 85–90%. This is because the RV method does not need to perform MP locating before NLOS identification can be carried out. However, its performance reduces when the number of hearable measurements is increased. The proposed method performs best and stable in all scenarios. This is because the last location information and step length is introduced to estimate the location of the MP before the LOS/NLOS measurement detection. This step makes the detection method more reliable, therefore it achieves better performance.

5.4 Location Accuracy

The goal of a wireless location system is to accurately localize



(a) LOS > 2



(b) LOS = 2

Fig. 10 Location error (m^2).

a user. In this subsection, we evaluate the location estimation by using location error. Location error is defined as the difference between the user's pre-determined location route and the estimated location route.

Figure 10 (a) shows the simulation results for location errors evaluated by different methods when the number of detected LOS measurements is more than three. From the figure, we see that the proposed method that only uses LOS measurements with the LS method performs best. It also outperforms the proposed method that uses the combination of measurements. LS performs worst, while WLS performs plain, as the number of TDOA measurement increases. For instance, when there are six TDOA measurements, four are detected as LOS measurements. The location error using the proposed method and in the first evaluation is about 4.2 m, while the second evaluation is 6.9 m. One reason why combination performs worse than only LOS measurements is that even if the last position and step length are used as supplementary LM and measurements in location estimation, the initial location is actually based on the average results of several WLS steps, i.e., the accuracy of the initial location impacts on the location accuracy. Therefore, the result that only uses LOS measurements performs better.

Figure 10 (b) shows the simulation results for location errors evaluated by different methods when the number of detected LOS measurements is less than three. We see that the location estimation using the LS method performs worst, and the proposed method with a combination of measurements performs best. The result is clear when the number of NLOS measurements increases. The combination provides more measurements when the hearable LOS measurements are less than three. WLS methods perform less than the combination but steadily, this is because that the NLOS/LOS detection also performs worse as shown in Section 5.2, if the same initial location is provided.

6. Conclusions and Future Works

In this paper, we proposed a new integration location method to solve the NLOS problem in a wireless TDOA location system. Simulation results show that LOS/NLOS measurements detection ratio is improved when the user's step length and count from built-in sensors of a mobile phone are used. Simulation results also show that using the user's step length and counts, location estimation error can be reduced when two LOS measurements are detected in a LOS/NLOS measurements combined TDOA location system. The drawback of the proposed method is that performance of location errors depends on the number of detected LOS measurements. When two LOS measurements are detected, location errors are reduced. To reduce location estimation error in the situation where the number of LOS/NLOS is 0LOS/3NLOS and 1LOS/2NLOS will be a part of our future work.

References

[1] Smith, A., Balakrishnan, H., Goraczko, M. and Priyantha, N.: Tracking Moving Devices with the Cricket Location System, *Proc. Mobisys 2004* (2004).

[2] Rudafshani, M. and Datta, S.: Localization in Wireless Sensor Networks, *Proc. IPSN 2007*, pp.51–60 (2007).

[3] Zhang, G., Krishnan, S., Chin, F. and Chung, K.C.: UWB MultiCell Indoor Localization Experiment System with Adaptive TDOA Combination, *Proc. VTC 2008-fall* (2008).

[4] Smith, A., Balakrishnan, H., Goraczko, M. and Priyantha, N.: Tracking Moving Devices with the Cricket Location System, *Proc. Mobisys 2004* (2004).

[5] Rudafshani, M. and Datta, S.: Localization in Wireless Sensor Networks, *Proc. IPSN 2007*, pp.51–60 (2007).

[6] Zhang, G., Krishnan, S., Chin, F. and Chung, K.C.: UWB MultiCell Indoor Localization Experiment System with Adaptive TDOA Combination, *Proc. VTC 2008-fall* (2008).

[7] Koozyt, Inc.: PlaceEngine, available from ⟨http://www.placeengine.com/⟩ (accessed 2010-05-17).

[8] Kourogi, M. and Kurata, T.: Personal positioning based on walking locomotion analysis with self-contained sensosrs and a wearable camera, *Proc. ISMAR 2003*, p.103 (2003).

[9] Fand, L., Antaklis, P.J., Montestruque, L.A., McMickell, M.B., Lemmon, M., Sun, Y., Fang, H., Koutroulis, I., Haenggi, M., Xie, M. and Xie, X.: Design of a wireless assisted pedestrian dead reckoning system – The NavMote experience, *IEEE Trans. Instrum. Meas.*, Vol.54, No.6, pp.2342–2358 (2005).

[10] Stirling, R., Fyfe, K. and Lachapelle, G.: Evaluation of a new method of heading estimation for pedestrian dead reckoning using shoe mounted sensors, *J. Navigation*, *Royal Society of Navigation*, Vol.58, No.1, pp.31–45 (2005).

[11] Pombinho, P., Afonso, A.P. and Carmo, M.B.: Indoor positioning using a mobile phone with an integrated accelerometer and digitial compass, *INForum* (2010).

[12] Steinhoff, U. and Schiele, B.: Dead reckoning from the pocket – An experimental study, *Proc. PerCom* (2010).

[13] Kamisaka, D., Muramatsu, S., Iwamoto, T. and Yokoyama, H.: Design and Implementation of Pedestrian Dead Reckoning System on a Mobile Phone, *IEICE Trans. Inf. and Syst.*, Vol.E94. No.6, pp.1137–1146 (2011).

[14] Chen, P.C.: A non-line-of-sight error mitigation method in location estimation, *IEEE Wireless Communications and Networking Conference* (*WCNC 1999*), Vol.1, pp.316–320 (1999).

[15] Caffery, J.J.: A new approach to the geometry of TOA location, *Proc. IEEE Veh. Technol. Conf.*, Vol.4, pp.1943–1949 (2000).

[16] Wann, C.D. and Hsueh, C.S.: NLOS Mitigation with Biased Kalman Filters for Range Estimation in UWB Systems, *Proc. IEEE TENCON 2007* (2007).

[17] Chao, W.K. and Lay, K.T.: NLOS Measurement Identification for Mobile Positioning in Wireless Cellular Systems, *Proc. IEEE VTC Fall*, pp.1965–1969 (Sep. 2007).

[18] Venkatesh, S. and Buehrer, R.M.: NLOS Mitigation Using Linear Programming in Ultrawideband in Location-Aware Networks, *IEEE Trans. Vehicular Technology*, Vol.56, pp.3182–3198 (2007).

[19] Ma, C.L., Klukas, R. and Lachapelle, G.: A Nonline-of-Sight Error-Mitigition Method for TOA Measurments, *IEEE Trans. Vehicular Technology*, Vol.56, No.2 (Mar. 2007).

[20] Yu, K. and Guo, Y.J.: NLOS Error Mitigation for Mobile Location Estimation in Wireless Networks, *IEEE 65th Vehicular Technology Conference, VTC2007-Spring*, pp.1071–1075 (2007).

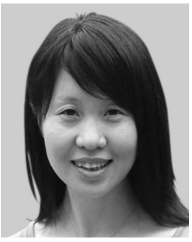
[21] Ouyang, R.W. and Wong, A.K-S.: An Enhanced TOA-based Wireless Location Estimation Algorithm for Dense NLOS environments, *Proc. Wireless Communications and Networks Conference* (2009).

[22] Alsindi, N.A., Alvai, B. and Pahlavan, K.: Measurement and Modeling of Ultrawideband TOA-based Ranging in Indoor Multipath Environments, *IEEE Trans. Vehicular Technology*, Vol.58, No.3 (Mar. 2009).

[23] Lui, K.W.K., So, H.C. and Ma, W.-K.: Maximum A Posteriori Approach to Time-of-Arrival-Based Localization in Non-Line-of-Sight Environment, *IEEE Trans. Vehicular Technology*, Vol.59, No.3, pp.1517–1523 (2010).

[24] Changlin, J.M., Klukas, R. and Lachapelle, G.: An enhanced two-step least squared approach for TDOA/AOA wireless location, *Proc. IEEE International Conference on Communications*, pp.987–991 (May 2003).

[25] available from ⟨http://en.wikipedia.org/wiki/Chauvenet's_criterion⟩.



Mingmei Li received her Ph.D. degree from the Graduated University for Advance Studies in 2007, and M.S. degree from Harbin Institute of Technology 2002 respectively. From 2007–2009, she was a researcher at the University of Tokyo. She joined KDDI R&D Laboratories Inc. in 2009 and engaged in research and development on ubiquitous computing, indoor location system, and wireless sensor networks. Her current research interests include future communication architecture, and personal lifelog technology. She is a member of the IEICE.

Naoki Imai was born in 1974. He received his M.E. and Ph.D. degree from the University of Tokyo in 2000 and 2003 respectively. After joining KDDI in 2003, he engaged in R&D in the field of ITS (Intelligent Transport Systems) and session mobility on IMS (IP Multimedia Subsystem). Currently, he is working in Multiple Access and Services Planning Department.

Kiyohito Yoshihara is a member of Green and M2M Application Laboratory, KDDI R&D Laboratories Inc., Since joining the Labs in 1995, he has been engaged in research on network algorithm, network management and operations. He received his B.E., M.E. and Ph.D. degrees from Tokyo Institute of Technology in 1993, 1995 and 2004, respectively.