Implementation Procedure of Wireless Signal Map Matching for Location-Based Services

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Abstract—*To mitigate the effects of non-line-of-sight error in terrestrial wireless location systems, a wireless signal map matching concept was recently introduced. The key concept of the wireless signal map matching is the automatic extraction of relationship between an electronic map representing ideal world and the fully-populated anonymous user distribution representing distorted world. This paper introduces an implementation procedure of the wireless signal map matching method. A simulation results demonstrates performance improvement that can be obtained by the proposed method.*

Keywords—*non-line-of-sight-error, distribution, correction*

I. INTRODUCTION

Location-Based Service (LBS) has recently gained a considerable amount of attention from both academia and industry. LBS, in a word, can be summarized as the electronic contents service that is somehow related to user location. Currently reported application areas of LBS include location-based information services, route direction assistance, gaming, resource management, fleet tracking, security, location-based billing, and e-commerce. Since accurate, reliable, and secure provision of user position should be guaranteed for effective LBS, Positioning Technologies (PTs) that compute user position estimates are considered as the core technology of LBS. For the reason, there is an extensive literature dealing with PTs. By investigating the open literature on PTs, it can be found that only a few PTs act as basis for many possible LBS applications.

Based on the source of signal, the currently-available PTs are basically classified into two groups: satellite-based methods and terrestrial network-based methods. The satellite-based methods based on the signals transmitted by GPS, GLONAS, or Galileo. The terrestrial wireless location systems are based on various types of network measurements including fingerprint, Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and Signal Strength (SS).

In spite of the accuracy benefits of satellite-based methods, considerable attention is currently being paid to terrestrial network-based methods. The reason is that they utilize only generic network-oriented measurements, often do not require hardware modification of User Equipment (UE), are deployable where demand is greatest (e.g. in urban areas), generally have a lower power consumption, and can achieve shorter Time-To-First-Fix with no a priori position information needed. However, it seems that there are three key problems in implementing the network-based PTs for advance LBS. They are privacy, hearability, and Non-line-Of-Sight (NLOS) error.

It is expected that most of requests for LBS would be invoked from urban environments. In spite of the measurement diversity, most of network-based measurements suffer from Non-Line-Of-Sight (NLOS) error in dense urban areas. It is likely that NLOS error can cause positioning errors of up to hundreds of metres in urban environments.

Extensive investigations have been carried out during the past decades to mitigate NLOS error using, for example, probability density function models [1], NLOS detection and de-weighting methods [2,3,4], constrained optimization methods [5,6,7], NLOS extraction at known positions [8], and database correlation method [9,10,11]. Each of the existing methods can be largely categorized into a filter-based method [1-7] and a survey-based method [8-11].

Among the two categories of the NLOS mitigation methods, the survey-based method seems to bear more possibility to improve practical positioning accuracy since it is based on real measurement statistics. The survey-based method consists of two phases; preparation phase and service phase. Fig. 1 illustrates preparation phase and service phase of a database correlation method as an example of the survey-based methods. When a client's measurement arrives, it is correlated with the surveyed measurement to generate a

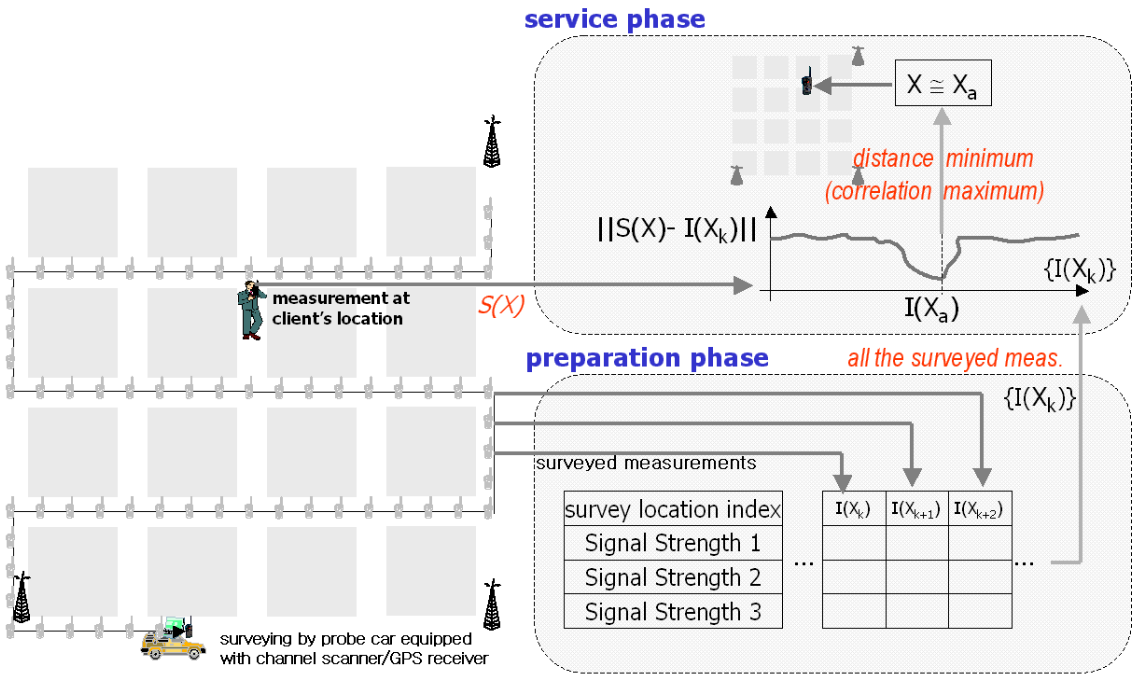

Fig. 1 An implementation procedure for database correlation method

distance (correlation) profile. A minimum (maximum) value appears in the distance (correlation) profile when a surveyed location is nearest to the client location.

In the survey-based methods, achievable accuracy improves as the number of surveyed location increases. However, special instruments and extensive labor are required to get sufficient measurement statistics. In addition, considerable computation is required to respond a client's location request. To eliminate the need for expensive outdoor surveying and to reduce computational burden in responding a location request, a new wireless signal map matching (WSMM) concept was recently introduced [12]. Extending the previous study, this paper introduces an implementation procedure of the WSMM. By a simulation result, benefits of the proposed WSMM is demonstrated.

II. Wireless Signal Map Matching

The key idea of the WSMM is the automatic extraction of relationship between an electronic map representing ideal world and the fully-populated anonymous user distribution representing distorted world. Thus, the preparation of WSMM starts by sampling bulks of measurements within a specific area as shown in Fig. 2. During the preparation phase, unnecessary or unhealthy measurements are screened out. The remaining measurements are stored to a measurement database (MDB). During this phase, measurements sampled from different hardware standards are filtered out by handset model.

Like the conventional survey-based method, the proposed WSMM consists of two operational phases: preparation and service phases. During the preparation phase as shown in Fig. 3, a telegeoinfomatics server needs to communicate with radio network controllers or their equivalents to build up bulks of measurements. After sufficiently large data is gathered, the non-line-of-sight error correction maps are generated and the preparation phase is finished. After the preparation phase, the service phase begins . During the service phase, the pre-computed non-line-of-sight error correction maps are utilized to respond user request instantaneously as shown in Fig. 4.

The most important prerequisite for the proposed WSMM is the data structure for sample network measurements and the extraction of reference measurements from large amount of sampled measurements. The purpose of WSMM data structure design is to facilatate efficient extration of reference measurements from all the sampled network measurements. Thus, a well-designed data structure for WSMM should contain all the data fields related to the timing, accuracy, and quality information for position estimation. A simplest data structure for the WSMM is illustrated in Fig. 2.

If there is no NLOS error in the measurements, estimated user positions by applying a proper TDOA algorithm to the stored MDB would be distributed in the neighborhoods of actual roads as shown by black points of Fig. 5 though they are affected slightly by measurement geometry, noise, and fading effects. However, occurance of NLOS error is highly probable in dense urban area where a lot of large buildings

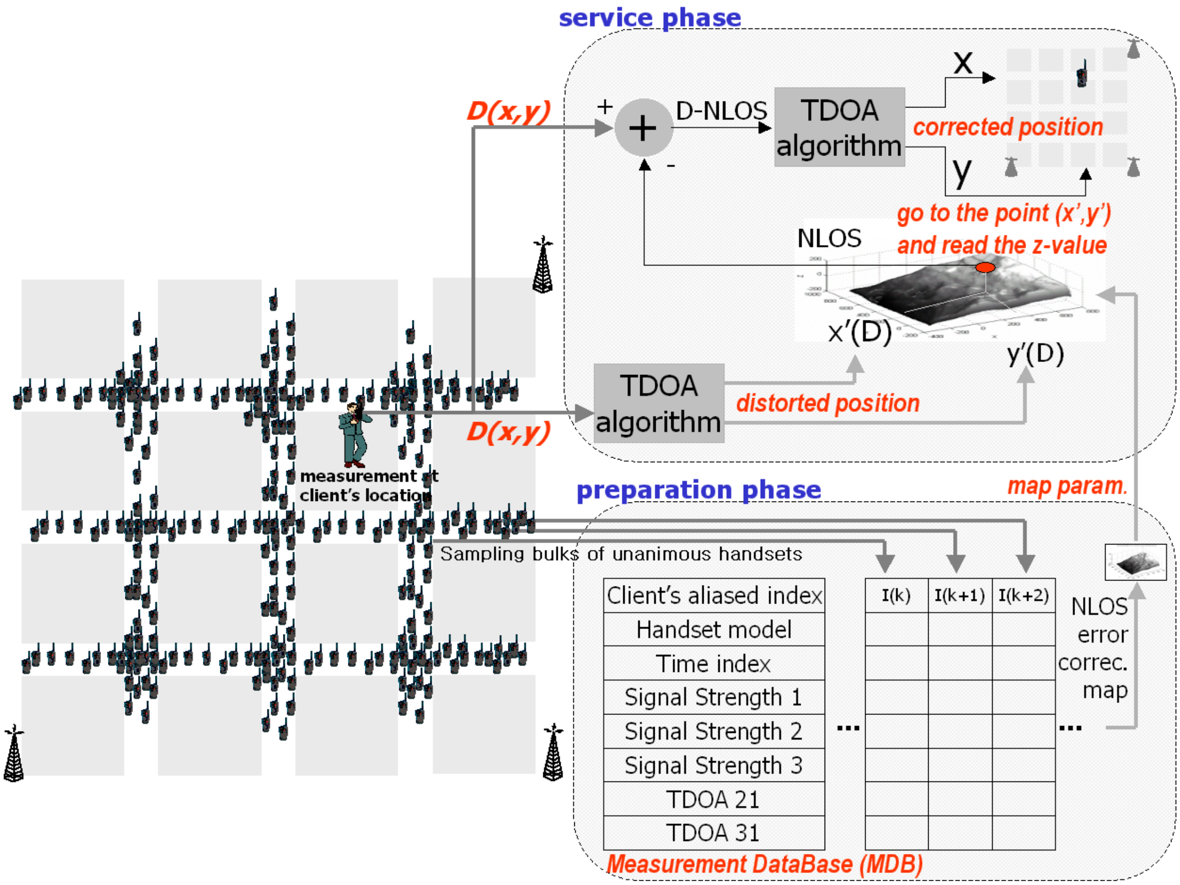

Fig. 2 An implementation procedure for wireless-signal map-matching method

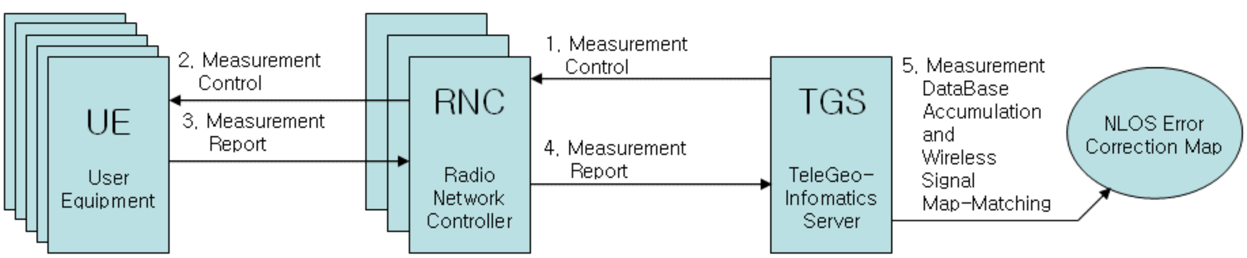

Fig. 3 Data flow during the preparation phase of wireless-signal map-matching : building measurement database for non-line-of-sight error correction map generation

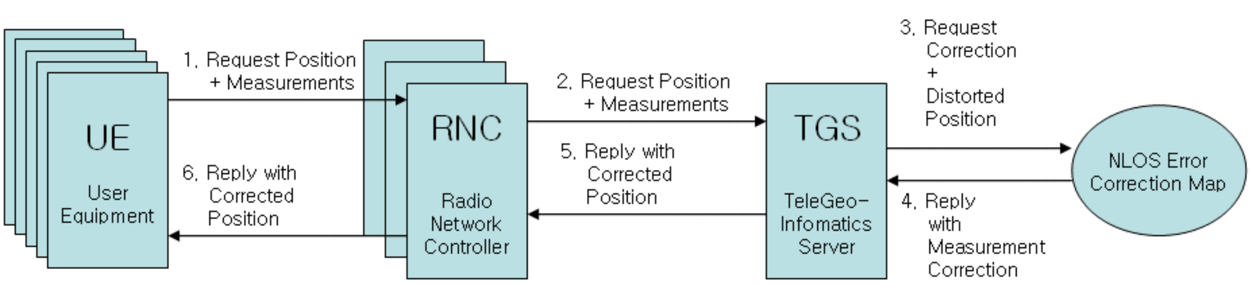

Fig. 4 Data flow during the service phase of wireless-signal map-matching : instantaneous response after user request

are present. As a result, computed user distribution appears like gray points of Fig. 5.

To extract reference measurements for WSMM, a feature map should be constructed. For this purpose, the domain where the distorted user distribution is plotted is gridized by multiple rectangles. A representative example of feature map is a smoothed population surface map. Fig. 6 shows the gridized population surface as a prerequisite for the smoothed population surface. As shown in Fig. 6, road segments and road junctions can be recognized by non-zero height values though noisy. To eliminate noise fluctuations, a two-dimensional Gaussian filter algorithm [13] is applied to the gridized population surface. As a result, the smoothed population surface is obtained as shown in Fig. 7.

Assume that a TDOA measurement $z(X(t))$ between node B2 and node B1 with its true position $X(t)=[x(t)\ y(t)]^T$ is obtained. If we denote $X_{B1}=[x_{B1}\ y_{B1}]^T$ and $X_{B2}=[x_{B2}\ y_{B2}]^T$ as the known coordinates of node Bs, a TDOA measurement $z(X(t))$ sampled at location X at time t satisfies the following relationship.

$$\begin{aligned} z(X,t) &= \|X(t)-X_{B1}\| + \|X(t)-X_{B2}\| + NLOS(X) + v(X) \\ &= \|X(t)-X_{B1}\| + \|X(t)-X_{B2}\| + h(X)\beta + v(X) \end{aligned} \tag{1}$$

where β indicate the spatial structure of NLOS error, $h(X)$ is the observation matrix for β, and $v(X)$ indicates the remaining smaller error sources. If the spatial structure β of the NLOS error is known as a linear trend or a quadratic trend, $h(X)$ and β in Eq. (1) can be rewritten as follows.

linear trend:

$h(X) := [1\ x\ y\ ]$,

$\beta := [\beta_0\ \beta_1\ \beta_2\ ]$

quadratic trend:

$$h(X) := [1\ x\ y\ x^2\ y^2\ xy],\ \beta := [\beta_0\ \beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5] \tag{2}$$

In both cases, β_0 indicates the bias term in the spatial structure of NLOS error.

If a road junction is identified as shown in Fig. 7, a set of reference information can be extracted. The reference information set consists of the measurement $z(X(t))$, distorted position $\hat{X}(t)=[\hat{x}(t)\ \hat{y}(t)]^T$, and the true position $X(t)=[x(t)\ y(t)]^T$ of the road junctions. Since the true distances from X to X_{B1} and X_{B2} can be computed, it is possible to extract NLOS measurement $\tilde{n}(X)$ as follows.

$$\begin{aligned} \tilde{n}(X) &:= z(X) - \|X - X_{B1}\| + \|X - X_{B2}\| \\ &= h(X)\beta + v(X) \end{aligned} \tag{3}$$

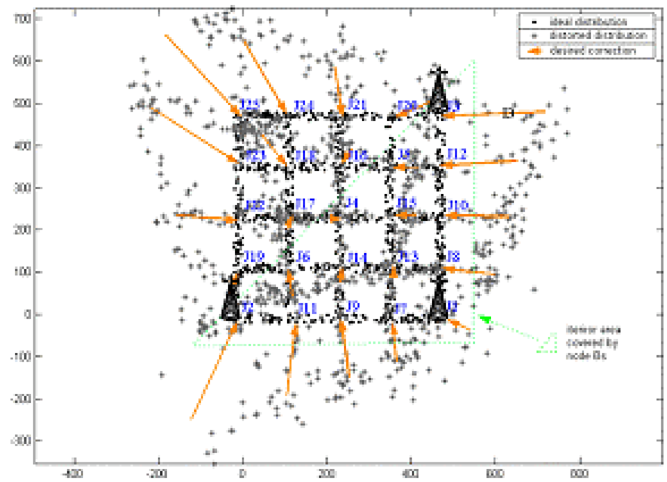

Fig. 5. Ideal and distorted user distributions

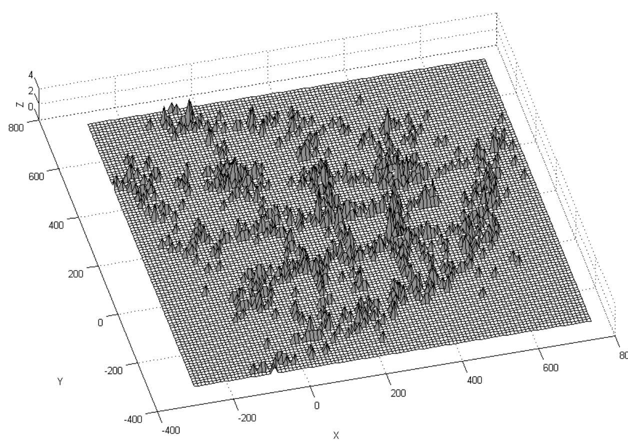

Fig. 6 Gridized population surface based on distorted user distribution

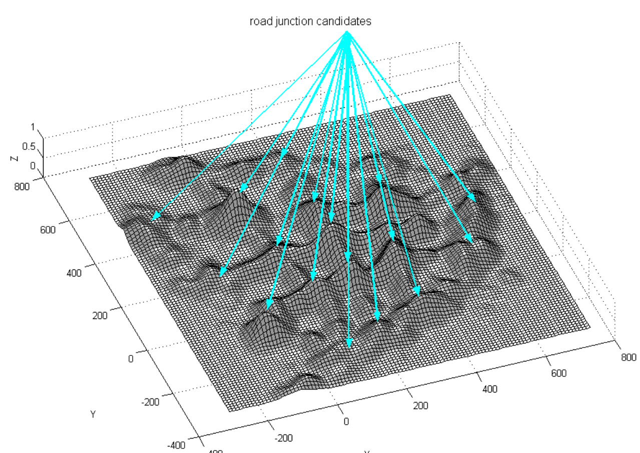

Fig. 7 Smoothed population surface as a feature map

Stacking the NLOS measurements at different road junctions into a vector, the following vector equation is obtained.

$$\widetilde{N} = H\beta + V \tag{4}$$

$$\widetilde{N} := \begin{bmatrix} \widetilde{n}(X_1) \\ \widetilde{n}(X_2) \\ \vdots \\ \widetilde{n}(X_J) \end{bmatrix},\ H := \begin{bmatrix} h(X_1) \\ h(X_2) \\ \vdots \\ h(X_J) \end{bmatrix}, V := \begin{bmatrix} v(X_1) \\ v(X_2) \\ \vdots \\ v(X_J) \end{bmatrix}. \tag{5}$$

where X_j and $\widetilde{n}(X_j)$ denote the j -th identified road junction and its associated NLOS measurement, respectively.

At the reference points (road junctions) where the related reference measurements exist, the NLOS error can be directly extracted. Unfortunately, no matter how densely reference measurements are identified, they cannot cover continuous area. If two measurements sampled at different but adjacent points show similar characteristics, the NLOS errors at non-reference points can be spatially extrapolated from the those measured at reference points. For this purpose, any spatial processing algorithm such as nearest neighbor, inverse distance to a power, radial basis function, spline, Kriging, minimum curvature, polynomial regression, spatial Kalman filtering can be utilized [14-18].

Among the various spatial processing algorithms, Kriging shows most attractive characteristics than others since it is based on well-developed statistical theory for geospatial analysis. By the universal Kriging algorithm[15], the NLOS estimate $\hat{n}_0$ at arbitrary position X_0 given J reference measurements $\{\widetilde{n}(\hat{X}_j)\}_{j=1,2,\cdots,J}$ can be estimated as follows:

$$\hat{\beta} = \left(H^T C_1^{-1} H\right)^{-1} H^T C_1^{-1} \widetilde{N}$$

$$\hat{n}(X_0) = c_0^T C_1^{-1}\left[\widetilde{N} - H\hat{\beta}\right] + h(X_0)\hat{\beta} \tag{6}$$

where

$$c_0 := \begin{bmatrix} \gamma(X_0, X_1) \\ \gamma(X_0, X_2) \\ \vdots \\ \gamma(X_0, X_J) \end{bmatrix}$$

$$C_1 := \begin{bmatrix} \gamma(X_1,X_1) & \gamma(X_1,X_2) & \cdots & \gamma(X_1,X_J) \\ \gamma(X_2,X_1) & \gamma(X_2,X_2) & \cdots & \gamma(X_2,X_J) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma(X_J,X_1) & \gamma(X_J,X_2) & \cdots & \gamma(X_J,X_J) \end{bmatrix}$$

$$\gamma(X_i, X_j) = \frac{1}{2} Var\left[v(X_i) - v(X_j)\right]: \text{variogram} \tag{7}$$

III. SIMULATION

To verify the effectiveness of the WSMM method, a simulation is performed. Since SS values drop down largely if wireless signals penetrate building walls, the measurement sets corresponding to building insides can be effectively filtered out. For the reason, a uniform user distribution on road segments in a Manhattan-like urban environment is generated as shown in Fig. 8. To generate the true TDOA , three node B locations are assumed as shown in Fig. 8. By adding NLOS error and noise terms to the true range difference, the TDOA measurements are generated. Since three node Bs are established, two TDOA measurements representing TDOA21 and TDOA31 are available for each point shown in Fig. 8. Fig. 9 and Fig. 10 depicts the injected NLOS error and noise on ideal domain.

As a result of the WSMM algorithm, NLOS correction maps are produced. Since this simulation considers three node Bs, two NLOS error correction maps are generated. Fig. 11 shows one of the two correction maps, i.e., the NLOS error correction map for the TDOA measurements with respect to node B2 and node B1. By comparing the injected NLOS error in Fig. 9 with the estimated NLOS error in Fig. 11, it can be concluded that the proposed WSMM is quite effective.

To provide an insight how effective the proposed WSMM is, error distances between estimates and true user positions are computed. As a result, the cumulative error distribution diagram of Fig. 12 is obtained. As shown in Fig. 12, 82 percent of users are within 50 m error distance with the WSMM while 47 percent of users are within the same error distance.

IV. CONCLUSION

An implementation procedure of wireless signal map matching method is introduced for calibrating non-line-of-sight error in urban environments. It is explained how the distorted user distribution based on sampled measurements are utilized to generate correction maps of non-line-of-sight error. A simulation result demonstrates that the propose method is efficient in reducing the effects of non-line-of-sight error.

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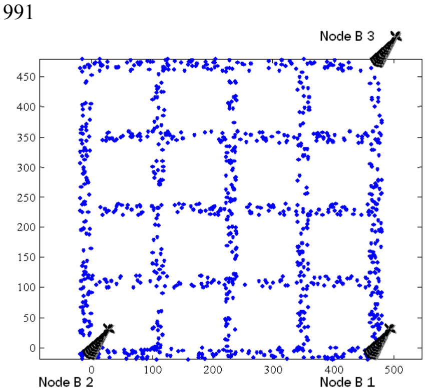

Fig. 8 Ideal user distribution on road segments in a Manhattan-like urban environment

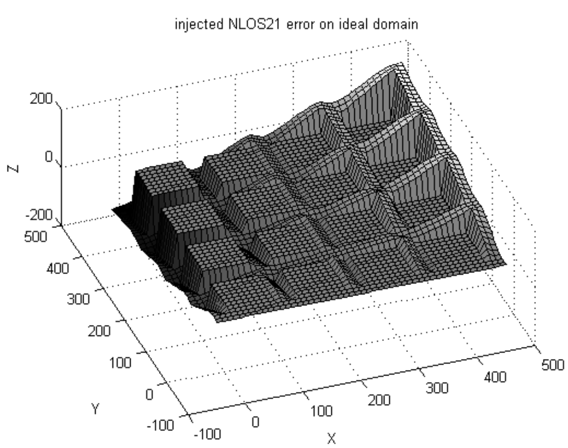

Fig. 9 Injected TDOA21 non-line-of-sight error on ideal domain

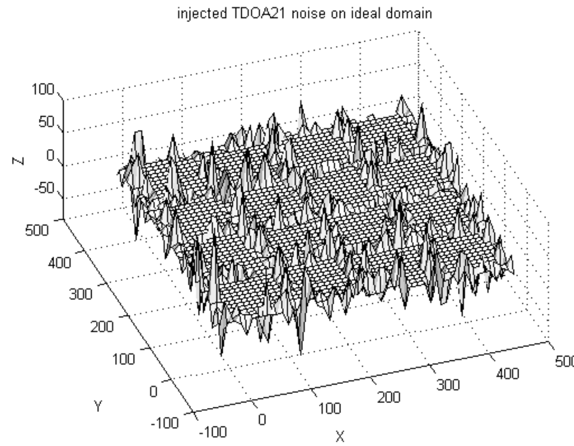

Fig. 10 Injected TDOA21 noise on ideal domain

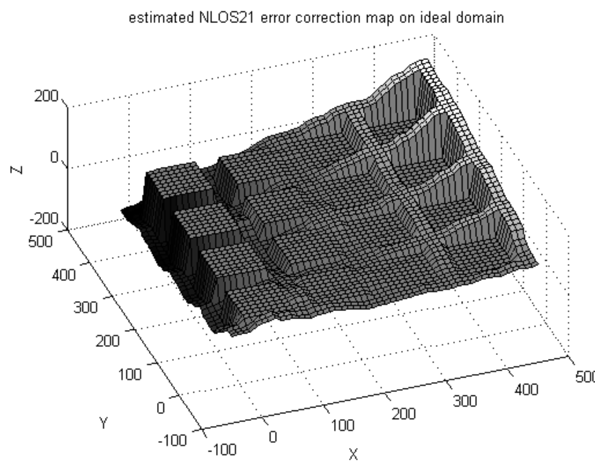

Fig. 11 Estimated TDOA21 non-line-of-sight error by wireless signal map matching

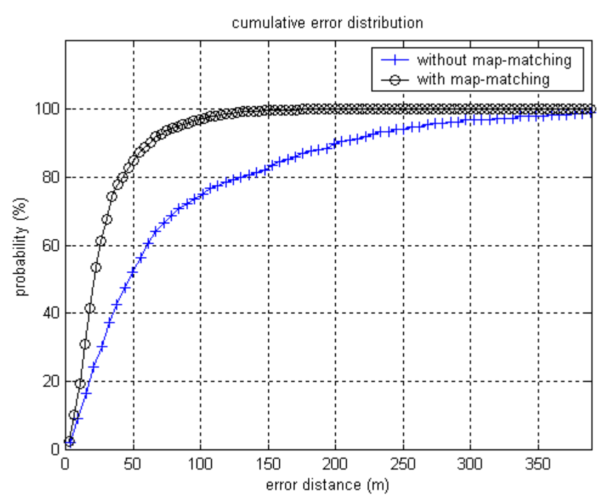

Fig. 12 Cumulative error distribution with and without wireless signal map matching