A Framework for Calibrating NLOS Error To Support LBS in Urban Environments

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BIOGRAPHY

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Chris Rizos holds a B.Surv. and Ph.D., both obtained from The University of New South Wales. He has been an academic staff member of the School of Surveying (renamed the School of Geomatic Engineering in 1994) since 1987, and is presently a Professor. He has been Chair of Commission 4 "Positioning & Applications" of the International Association of Geodesy since mid-2003 and has published over 150 papers, as well as having authored and co-authored several books relating to GPS and positioning technologies. He is leader of the Satellite Navigation and Positioning (SNAP) group at UNSW, specialising in precise static and kinematic applications of the GPS technology and new positioning technologies.

ABSTRACT

This paper proposes a new wireless-signal map-matching method for calibrating non-line-of-sight error in urban environments. As compared with the conventional map-matching methods that utilize a continuously-tracked sigle user trajectory, the proposed map-matching method utilizes bulks of different user locations for comparison with ideal map information. By appying the proposed method to the sampled network measurements, non-line-of-sight error correction maps on distorted position domain are generated. Once the non-line-of-sight error correction maps are constructed, they can be applied to the same type of measurements thereafter. Since the proposed wireless-signal map-matching method can be installed either inside or outside the core network structure and applicable to any type of network measurements such as time-of-arrival, time-difference-of-arrival, and angle-of-arrival, it bears good implementation flexibility. A simulation result assuming a typical dense urban environment demonstrates benefits of the proposed wireless-signal map-matching method.

INTRODUCTION

Location-Based Service (LBS), in a word, can be summarized as the electronic contents service that is somehow related to user location. Due to large revenue expected from it in near future [1-3], LBS has recently gained a considerable amount of attention from both academia and industry. 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 [4]. 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) [5].

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 utilise 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. It is expected that most of requests for LBS would be invoked from urban environments.

Unfortunately, most of network-based measurements suffer from Non-Line-Of-Sight (NLOS) error in dense urban areas. The NLOS error problem occurs when direct signal paths between mobile and node Bs are mostly obstructed by buildings and other structures as shown in Fig. 1 so that the measured range information always contains positive error. It is likely that NLOS error can cause positioning errors of up to hundreds of metres in urban environments. For the reason, extensive investigations have been carried out during the past decades to mitigate NLOS error using, for example, probability density function models [6], NLOS detection and de-weighting methods [7-9], constrained optimization methods [10-12], NLOS extraction at known positions [13,14]. However, NLOS error is still the single most critical issue for advanced LBS, having not yet been satisfactorily resolved.

This paper introduces a new map-matching method for calibrating NLOS error in urban environments. Though conventional map-matching methods have added values to map information in improving positioning accuracy in addition to Graphic User Interface (GUI), it seems that their focus has been mostly laid on a continuously- tracked single user trajectory [15-17]. The key idea of the patent-pending Wireless-Signal Map-Matching (WSMM) algorithm is the extraction of relationship between an electronic map representing ideal world and the fully-populated anonymous user distribution representing distorted world. Thus, the ideal map information is not compared to a continuously-tracked single user trajectory but compared to bulks of different user locations. As compared with the conventional NLOS extraction methods utilizing the location measurement units (LMUs) or instrument vehicles [13,14], the proposed algorithm does not require additional hardware whose position is computed by GPS. By installing the WSMM algorithm flexibly either inside or outside the core network

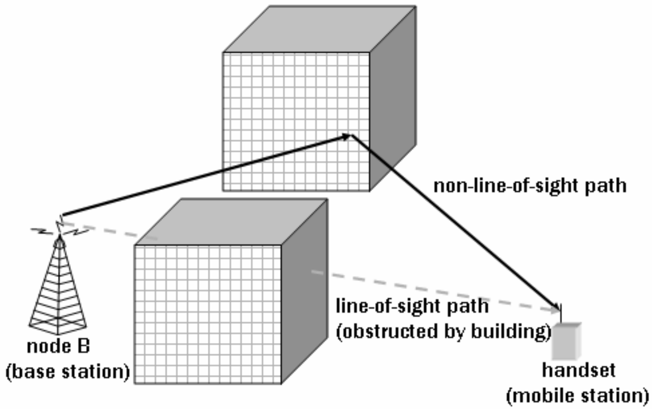


Fig. 1 Configuration of non-line-of-sight error occurence

infra structure, NLOS error correction maps are automatically generated.

WIRELESS-SIGNAL MAP-MATCHING

The characteristics of the proposed WSMM algorithm can be described by a compound word “telegeoinfomatics” which means that bulks of wireless signals are map-matched by statistical characteristics. Since terrestrial wireless location systems enables bulks of sampling with respect to multiple users at different locations, fully populated user distribution, though distorted by the NLOS error, has become practically possible. By comparing the geometric features of distorted user distribution with those of ideal map, NLOS-induced position error and each measurement’s NLOS error can be extracted. As a result, the proposed WSMM has two attractive advantages in mitigating NLOS error. One is that it does not require additional network element installation the other is that it eliminates human effort for surveying field data with special instruments. In this section, the proposed WSMM will be explained.

A. Measurement Database

The most important prerequisite for the proposed WSMM is the construction of Measurement DataBase (MDB). The MDB can be constructed by sampling the measurements of handset within the area of interest by core network infrastructure shown in Fig. 2. The sampled measurements are filled into a data structure that is designed for efficient MDB management. Fig. 3 shows a typical data structure for MDB construction. The data fields are categorized into user index, handset model, time index, location-related network measurements, and any LBS-related variables for which a spatio-temporal or a statistical surface map is desired. The location-related network measurements may comprise one or more of TDOA, Frequency Difference of Arrival (FDOA),

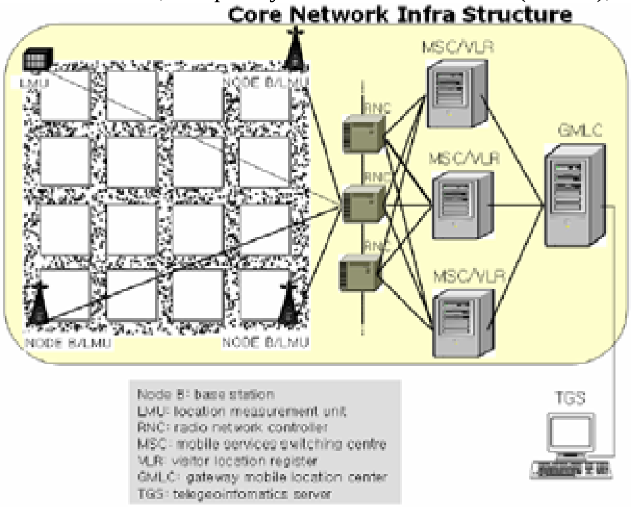


Fig. 2 Core network infrastructure for terrestrial wireless location systems

Alias for privacy (arbitrary index number)	I(1)	I(2)	I(3)		I(Np)
Handset model					
Time index					
TDOA (1:Nb-1)					
FDOA (1:Nb-1)					
TOA (1:Nb)					
FOA (1:Nb)					
AOA (1:Nb)				. . .	
TSS(1:Nb)					
RSS(1:Nb)					
SNR(1:Nb)					
Variables to be analyzed on either distorted or corrected spatio-temporal domain (NLOS error, NLOS rate, SS statistics, noise statistics, serviced LBS-type and its frequency)					
Temporary Results					

Fig. 3 Data structure for measurement database

TOA, Frequency Of Arrival (FOA), AOA, Transmitted Signal Strength (TSS), Received SS (RSS), Frequency Difference Of Arrival (FDOA), and Signal-to-Noise Ratio (SNR). In the LBS-related variable field, a fairly large application area can be considered. The variables to be analysed on either a distorted or corrected spatio-temporal domain may comprise one or more of NLOS error, NLOS rate, SS statistics, noise statistics, service LBS-type and its frequency. For example, variables for network resource management including SNR, SS, and communication amount can be stored for location-dependent statistical map generation. Also, variables to assess LBS and Intelligent Transportation System (ITS) can be stored to generate statistical map generation for traffic forecasting, requested LBS types, most-enquired restaurant type, and LBS-resultant billing.

B. Reference Measurement Extraction

The uncompensated NLOS errors in sampled measurements generate biased position estimates which constitute distorted user distribution compared with ideal map information as shown in Fig. 4. Though the amount of distortion can be reduced if proper signal model, environmental model, and processing technique are selected, the distortion is usually inevitable. If simplified NLOS by the 2-dimensional Dijkstra algorithm are added to normal TDOA measurements with noise terms, the distortion of estimated user distribution appears as shown by gray points of Fig. 4. Though the distortion of user distribution shown in Fig. 4 is resulted by utilizing TDOA measurements, the distortion is generally unavoidable in dense urban area even though other types of measurements are utilized including TOA, TDOA, AOA, and SS.

To recover the distorted distribution to the ideal distribution, any form of reference information is required. In the proposed algorithm, the reference information is formed by two techniques. One is the measurement characteristic classification and the other is the map feature extraction. The utilization of measurement characteristic classification is relatively simple. For this purpose, SS value of each MDB element is checked compared to a pre-defined threshold value. According to Hata –Okumura model [18] or COST 231 Walfisch-Ikegami model [19], SS value describes the distance between any transmitter and receiver with good accuracy if they are sufficiently adjacent so that there is no obstruction for line-of-sight condition. Thus, the measurement set which includes maximum SS with respect to some node B means that they are sampled near that node B. In these proxi-measurement sets, the effects of NLOS error would be small and their sampled position would approximately equals that of the corresponding node B.

Usually, the amount of reference information by the measurement characteristic classification would be not sufficient for NLOS error mitigation. To provide sufficient amount of reference information, map features should be extracted. If we consider a simple map that consists of nodes and links, any feasible map-matching techniques can be applied with respect to nodes, links, and node-link combined geometry [17]. Dense urban area is mostly composed of road

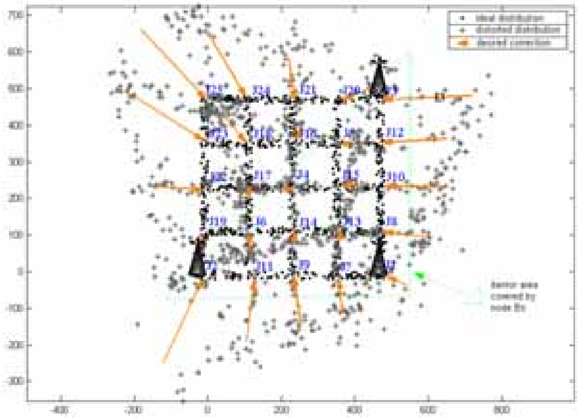


Fig. 4 Ideal user distribution and distorted user distribution by non-line-of-sight error

junctions, road segments, and buildings, where road junctions are stored as node, road segments are stored as links. Though any map feature is useful as reference information, an identified road junction is the easiest feature for map-matching.

To extract reference measurements by map features, two maps are utilized; an Ideal MAP (IMAP) and a Feature MAP (FMAP). The IMAP is used as the reference information for WSMM. Thus, it should accurately represent the real world and usually includes the coordinates of node Bs, buildings, and geometric features such as road junctions and links as shown in Fig. 5. The FMAP is a 3-dimensional surface map based on distorted user distribution computed by the MDB. The FMAP z-values represent the degree of confidence of their corresponding xy-positions as feature areas. For example, the higher the z-value is, the more possible its xy-position corresponds to a map feature.

Numerous candidates may be utilized as the FMAP including a population surface, a Dilution Of Precision (DOP) surface utilizing user points within a specific radius, and any possible measure surface that expresses the similarity between local user distributions with feature area patterns. In Fig. 6, a typical FMAP representing smoothed population surface is illustrated. As shown in Fig 6(b), the z-values corresponding to the distorted road junction locations show local maximums. By comparing the xy-positions of road junctions stored in the IMAP and the xy-positions with local maximum z-values in the FMAP, the distorted positions of road junctions are identified. For each identified xy-position of the FMAP, several measurement sets in the MDB can be found that corresponds to its neighbourhood as shown in Fig. 7.

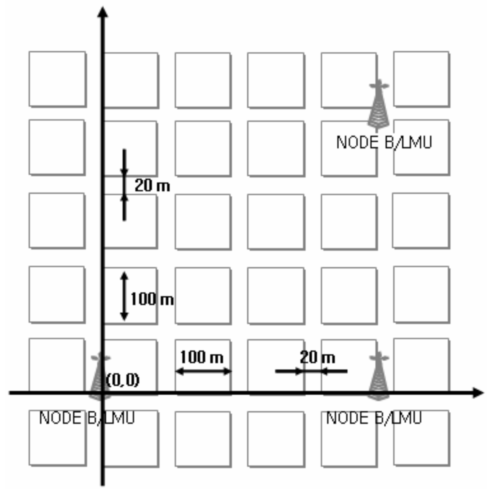
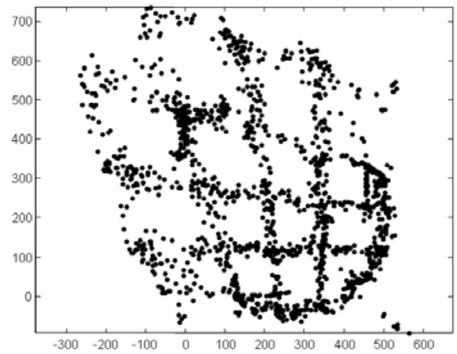
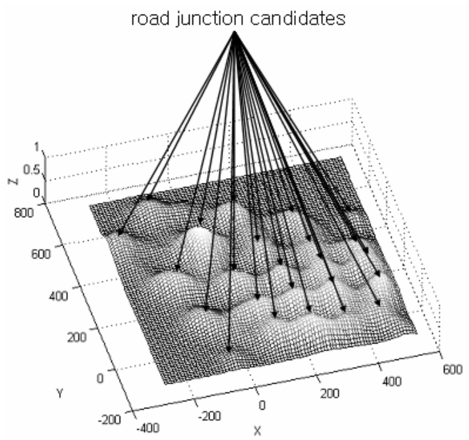


Fig. 5 An example of ideal map



(a) user distribution based on measurement database



(b) smoothed population surface as feature map

Fig. 6 An example of feature map computation

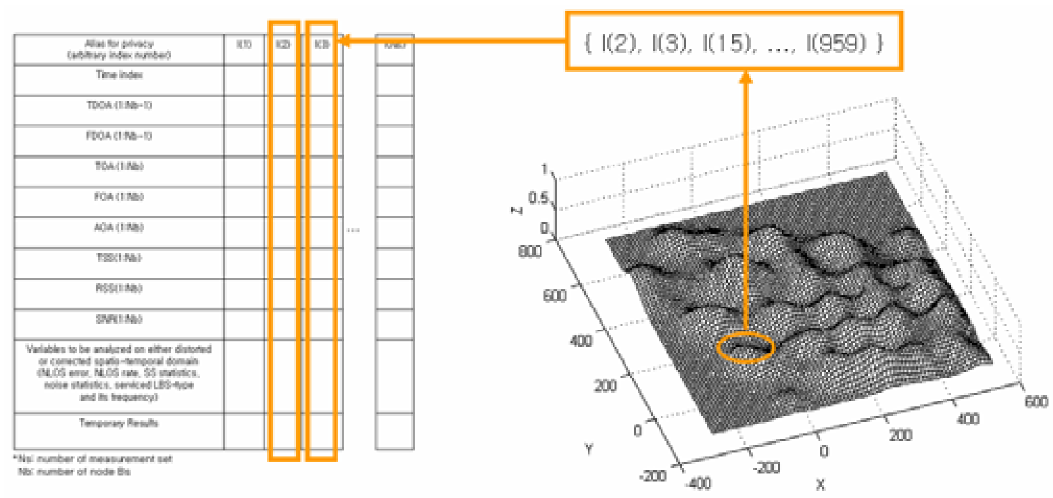


Fig. 7 Extraction of reference measurements from measurement database referencing feature map

C. Spatial Processing for Correction Map Generation

After the reference information to mitigate map distortion is extracted either by characteristic classification or by map feature, the derived reference information is utilized as a reference measurement. Since each reference measurement is related to a point on ideal (undistorted) domain and a point on distorted domain, NLOS error can be extracted effectively as follows. Assume that a TDOA measurement $\tilde{y}(X)$ between node B 2 and node B 1 with its true position $X = [x_u \; y_u]^T$ and distorted position $\hat{X} = [\hat{x}_u \; \hat{y}_u]^T$ is identified. If $X_{B1} = [x_{B1} \; y_{B1}]^T$ and $X_{B2} = [x_{B2} \; y_{B2}]^T$ are denoted as the known coordinates of the two node Bs, The TDOA measurement $\tilde{y}(X)$ satisfies the following relationship:

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

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

linear trend:

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

$$\beta := [\beta_0 \; \beta_1 \; \beta_2 \;] \quad (2)$$

quadratic trend:

$$h(X) := [1 \; x \; y \; x^2 \; y^2 \; xy]$$

$$\beta := [\beta_0 \; \beta_1 \; \beta_2 \; \beta_3 \; \beta_4 \; \beta_5] \quad (3)$$

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

At the reference points where the reference measurements are sampled, the NLOS error can be directly extracted. Unfortunately, no matter how densely the reference positions are distributed, they cannot cover continuous area that we are interested. If the variable of interest is statistically stationary in spatial domain any two variables sampled at different but adjacent points show similar characteristics, any spatial processing algorithm such as nearest neighbor, inverse distance to a power, radial basis function, spline, Kriging [20-23] can be used to obtain the variable estimates at non-reference points. Among the various spatial processing algorithms, Kriging is more attractive characteristics than others since it is based on statistical theory for geospatial analysis. From now on, a Kriging algorithm is taken as an illustrative example. For this purpose, the measurement equation shown in Eq. (1) for reference points is modified as follows.

$$z(X) := \tilde{y}(X) - \|X - X_{B1}\| + \|X - X_{B2}\| = h(X)\beta(X) + v(X), \quad (4)$$

where $z(X)$ indicates the newly defined NLOS measurement. Using the universal Kriging algorithm [21-23], the NLOS estimate $\hat{z}_0(X_0)$ at an arbitrary position X_0 given J reference measurements $\{\tilde{z}(X_j)\}_{j=1,2,\cdots,J}$ can be estimated as follows:

$$\hat{\beta}(X_0) = \left(H^T C_1^{-1} H\right)^{-1} H^T C_1^{-1} \tilde{Z}\ , \tag{5}$$

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

where

$$H := \begin{bmatrix} h(X_1) \\ h(X_2) \\ \vdots \\ h(X_J) \end{bmatrix}, \tag{7}$$

$$\tilde{Z} := \begin{bmatrix} \tilde{z}(X_1) \\ \tilde{z}(X_2) \\ \vdots \\ \tilde{z}(X_J) \end{bmatrix}, \tag{8}$$

$$c_0 := \begin{bmatrix} \gamma(X_0, X_1) \\ \gamma(X_0, X_2) \\ \vdots \\ \gamma(X_0, X_J) \end{bmatrix}, \tag{9}$$

$$C_1 := \begin{bmatrix} \gamma(X_1, X_1) & \gamma(X_1, X_2) & \cdots & \gamma(X_1, X_J) \\ \gamma(X_2, X_1) & \gamma(X_2, X_2) & \cdots & \gamma(X_2, X_J) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma(X_J, X_1) & \gamma(X_J, X_2) & \cdots & \gamma(X_J, X_J) \end{bmatrix}, \text{ and} \tag{10}$$

$$\gamma(X_i, X_j) = \frac{1}{2} Var\left[v(X_i) - v(X_j)\right]: \text{ variogram} \tag{11}$$

SIMULATION

To verify the effectiveness of the WMM concept, 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 (a). To generate the true TDOA , three node B locations are assumed. 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 (a). Fig. 8 (b) and 8 (c) depicts the injected NLOS error and noise on ideal domain. Due to the injected NLOS error and noise, the position estimates based on the TDOA measurements are not fitted to the well-arranged distribution shown in Fig. 8 (a) but to the severely-distorted distribution shown in Fig. 9 (a).

By applying the proposed WMM algorithm based on the reference measurements near node Bs, a less distorted user distribution shown in Fig 9 (b) is obtained. In identifying the reference measurements near node Bs, the SS values that indicates the range information from node Bs are utilized.

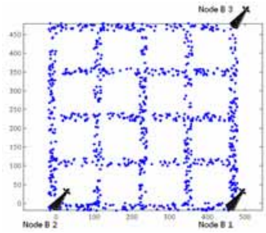
After the smoothed population surface of Fig 9 (b) is constructed, its local maximum points are compared to the road junction points on the ideal map. As a result, the reference measurement sets that correspond to the internal area of the node B triangle are identified. By applying the proposed WMM algorithm based on map features, a less distorted user distribution shown in Fig 9 (c) is obtained.

As a result of the WMM algorithm, NLOS correction maps on distorted domain are produced. Since this simulation considers three node Bs, two NLOS error correction maps are generated. Fig. 10 (a) shows one of the two correction maps, i.e., the NLOS error correction map for the TDOA measurements with respect to node B 2 and node B 1. As compared with the NLOS error correction map on distorted domain that can be practically utilized for positioning accuracy improvements, the NLOS error correction map on ideal domain is useful for performance assessment of the proposed WMM. Fig 10 (b) shows the NLOS error correction map on ideal domain. By comparing the injected NLOS error in Fig. 8 (b) with the estimated NLOS error in Fig. 10 (b), it can be concluded that the proposed WMM is quite effective.

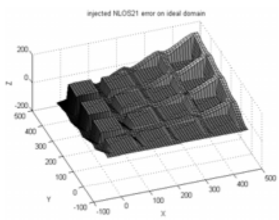
To provide an insight how effective the proposed WMM is, error distances between estimates and true user positions are computed. As a result, the cumulative error distribution diagram of Fig. 11 is obtained. In Fig. 11, two lines with the symbols ‘o’ and ‘+’ correspond to the cumulative error distribution with and without the proposed WMM, respectively. As shown in Fig. 11, 85 percent of users are within 50 m error distance with the WMM while 52 percent of users are within the same error distance.

CONCLUSION

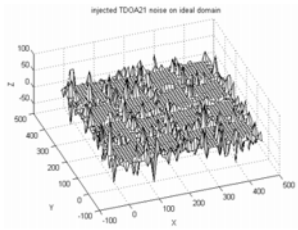
A new wireless-signal map-matching method is proposed for calibrating non-line-of-sight error in urban environments. For the proposed wireless-signal map-matching method, bulks of measurements from different user equipments are extensively utilized. To generate correction maps of non-line-of-sight error, distorted user distribution based on sampled measurements is compared with ideal map information. Various key concepts for the construction of correction map are explained including network structure, measurement sampling, data structure, reference information extraction, and spatial processing algorithm for NLOS correction-map generation. A simulation result demonstrated how positioning accuracy improves by the proposed wireless-signal map-matching method.



(a) ideal user distribution on road segments in a Manhattan-like urban environment

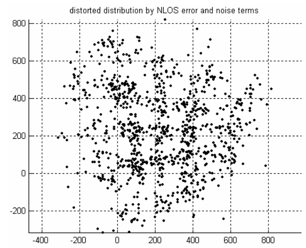


(b) injected TDOA21 NLOS error on ideal domain

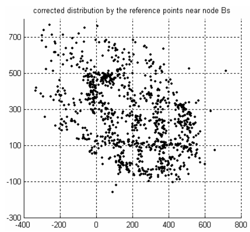


(c) injected TDOA21 noise on ideal domain

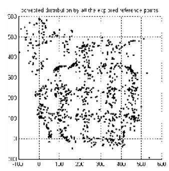
Fig. 8 Ideal user distribution and injected error terms



(a) no correction

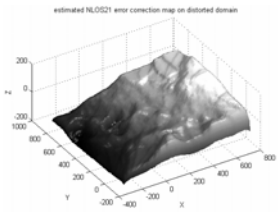


(b) correction by reference measurements near node Bs

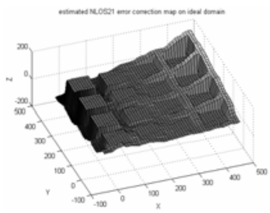


(c) correction by reference measurements extracted from map features

Fig. 9 Corrected user distribution by the proposed wireless map-matching

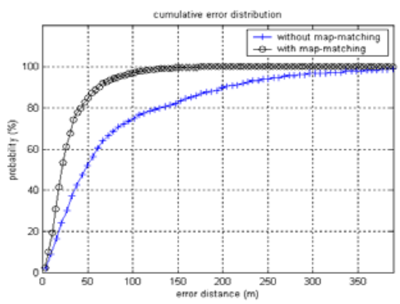


(a) correction map on distorted domain for practical implementation



(b) correction map on ideal domain for analysis

Fig. 10 Non-line-of-sight error correction map on distorted and ideal domains



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