

Chapter 71

Research on Multi-Source Fusion Based Seamless Indoor/Outdoor Positioning Technology

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Abstract GNSS has been applied widely. Yet because satellite signals are vulnerable and susceptible to blockage, the operability of GNSS in urban canyons are greatly hampered and GNSS even proves useless for indoor settings. This paper proposes system architecture for the integration of WLAN fingerprinting, visual positioning, baroreceptor-derived altitude estimation and GNSS for seamless indoor/outdoor positioning for vehicles and pedestrians. This architecture augments GNSS through the integration of terminal-side/network-side positioning and position/measurement domain. After temporal and spatial synchronization, data from each sensor is filtered by sub filters and then processed by the main filter. The purpose of these operations is to provide accurate and continuous estimates of positions. Tests conducted in the new technology center of CAS show that the architecture proposed can achieve seamless indoor/outdoor positioning, with a better accuracy performance than any single-source method as the former still maintains accuracy and continuity when the later generates noticeable errors. Calculation shows that multi-source fusion has an accuracy level of better than 1 m (outdoor)/3 m (indoor), hence capable of meeting users' demand for seamless indoor/outdoor positioning.

Keywords Seamless indoor/outdoor · Multi-source fusion · Decentralized kalman filtering

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71.1 Introduction

In recent years, with the development of information and sensor technology, there has been an increased interest in Location Based Service, or LBS, and a greater demand for navigation and positioning services in different contexts. GPS, the most prevalent navigation technology with the widest coverage, has been improved significantly. However, satellite navigation signals are vulnerable by nature, when interfered with or blocked, they will fail to provide continuous navigation services with accuracy especially in urban canyons and enclosed indoor settings which would greatly attenuate GNSS signals even to the point of invalidity. Against that backdrop, an integrated multi-source positioning technology for ubiquitous signals in both indoors and outdoors settings is an inevitable trend for navigation and positioning services as well as a key issue in the construction and development of a PNT system.

Many researchers have done a lot of work on multi-source fusion based navigation worldwide. Reference [1] synthetically analyses developing trend of indoor positioning techniques. Reference [2] adopts random signal to achieve positioning, and implements technique tests, which verify initial feasibility of navigation technique using random signal. Reference [3] synthetically analyses current wireless network based positioning techniques, concluding that due to effects of environment etc. on the signal strength, wireless technique is unable to provide high-precision positioning. Reference [4] combines methods of 2D and 3D to detect pedestrians. Reference [5] realizes fusion of RFID and supersonic methods via triangular positioning. Reference [6] adapts RSSI based indoor positioning algorithm, and derives path loss index estimation algorithm from wireless propagation loss model of indoor environment based on 4 fixed nodes. However, multi-source fusion based outdoor/indoor seamless positioning techniques aimed at multiple heterogeneous positioning methods still waits for further research.

Fusion and filter algorithm weighs heavily in multi-source fusion techniques. Aside from common Kalman filter technique [7, 8], particle filter [9, 10], neuron network [11], Bayesian estimation [12], maximum posteriori probability estimation [13] etc., many novel filter techniques are also being explored. Reference [14, 15] construct recursive model of sensing data to lower computing loads. Reference [16] proposes using Gaussian mixed model to detect pedestrian in laser imaging space. Reference [17] raises a method of fusion of different sensors. Reference [18] brings forward a semantics based fusion method according to Markov logic network. Reference [19] shows a new fusion method of information from multiple sensors, which theoretically realizes fusion of INS/COD/SAR system by means of ARTMAP neuron network and DS. References [20, 21] bring some new theories such as sparse representation and compressive sensing in visual tracking to solve problem of representation of human body characteristics. Throughout the researches on filter algorithms, no single filter algorithm can effectively solve the problem of optimal fusion of different sensors under different environments. In actual

implementation, proper selection of fusion and filter algorithm according to different elements such as sensor's categories, fusion positioning demands, resource consumption is suggested.

71.2 Sensor Classifications and Property Analysis

When ubiquitous signals from both indoor and outdoor settings are utilized for positioning, heterogeneity between sensors is a major constraint for the integration of multiple sources. Such heterogeneity is reflected in the following aspects:

- (1) Heterogeneity in the utilization of frequency spectrum resources as a result of differences in wireless spectrum properties;
- (2) Errors caused by different measuring methods and heterogeneity in environmental adaptiveness;
- (3) Diversity in interface designs and realization of relevant protocols for different networking technology;
- (4) Heterogeneity in time and space references;
- (5) Heterogeneity in the time of sampling and positions of measurement;
- (6) Variety in terminals and services;

Multiple positioning technologies which can be integrated are assorted based on common sensor types: GNSS and its augmented system are the most commonly used for geo-location both indoors and outdoors; while other supplementary methods can be categorized as measurement-based wireless positioning, fingerprint-based wireless positioning, vision-based positioning, temperature-based cognitive positioning and inertial navigation-based active positioning. Characteristics of and representative positioning methods for each positioning technology are presented below:

(1) Measurement-based wireless positioning technology

Measurement-based wireless positioning technology mainly refers to measurement methods based on distances, angles and time of arrival. Typical applications include TOA/TDOA, UWB ranging scheme, and CMMB-based geo-location.

Wireless signals employed by this type of positioning technology are mostly not specifically for navigation and positioning and are significantly stronger than GNSS signals. They feature good penetrability and do not require massive deployment of additional infrastructures. However, affected by factors such as time synchronization, measurement-based wireless positioning technology tend to lack accuracy and are susceptible to multipath and NLOS in urban crayons and indoor environment.

(2) Fingerprint-based wireless positioning technology

Fingerprint-based wireless positioning technology mainly refer to positioning methods that are based on fingerprint information including signal strength and that obtain a location estimation through finding a closest match for the current signal

strength measurement. Typical applications include WLAN and ZIGBEE positioning.

Fingerprint-based wireless positioning technology feature low equipment costs and is free from the effect of multipath and NLOS. Moreover, it does not require temporal simultaneity of transmitters, and is able to effectively deliver continuous positioning. On the other hand, it requires pre-measurement of signal strengths which will later serve as reference data. Additionally, it is vulnerable to changes in the environment.

(3) **Electro-optical measurement-based assistive positioning technology**

Electro-optical measurement-based assisted positioning technology refers to positioning which is assisted by photogrammetry, infrared detection, and laser measurement. Typical applications include laser sensors, infrared indoor positioning, and active/passive visual positioning.

This type of technology is good at environment exploration and delivering positioning estimates with high precision. It is user-friendly and free from the effect of multipath and NLOS both indoors and outdoors. On the other hand, it requires the deployment of measurement equipment. Devices such as laser sensors are costly and susceptible to light.

(4) **Meteorological effect-based cognitive positioning technology**

Meteorological effect-based cognitive positioning technology mainly refers to the determination of user's altitude through the measurement of barometric pressure, wind velocity and humidity. Altitude determination through barometric pressure is a typical application.

Baroreceptors employed by this type of positioning are low in cost, easy to apply and use simple algorithms. On the other hand, they are vulnerable to wind velocity and the environment. Moreover, accuracy is low.

(5) **Inertial navigation-based active positioning technology**

Inertial navigation-based active positioning technology mainly refers to the positioning technology assisted by users' devices such as gyroscopes and accelerometers to measure positions and speed.

Inertial navigation-based active positioning technology is convenient and effective; therefore, it has been adopted widely. However, errors increases as time drifts; therefore, there is a need to correct them real-time, implying that this technology cannot operate independently for long.

(6) **Geographic information-based matching technology**

Geographic information-based matching technology refers to the acquisition of high-precision information such as location and heading by comparing user information with pre-existing maps.

This type of technology is capable of providing location services with high precision, but it requires the establishment of an accurate database which takes time to build and must be updated real-time with changes in geographic locations. Moreover, querying can be time-consuming if a priori information is lacking.

71.3 Evaluation of Multi-Source Fusion Positioning

71.3.1 Definition of Seamless Positioning

Defined by demand, seamless positioning means seamless coverage of navigation and positioning areas; technically, it means seamless handover between different positioning methods; defined by terminals, it means seamless fusion of navigation and positioning information.

(1) Seamless coverage of navigation and positioning areas

Traditional GNSS is inadequate in terms of positioning accuracy and operability in dense urban areas and enclosed indoor environments where signals are susceptible to blockage and multipath effect. Multi-source fusion positioning technology, on the other hand, can meet positioning needs in different environments because of the combined coverage of each positioning method.

Coverage of navigation and positioning signals can be categorized as passive and active coverage. Passive coverage refers to the situation where users directly receive navigation and positioning signals from mobile positioning systems. These signals can be shared by multiple users. Active coverage refers to the situation where a user determines his/her location while he/she move by detecting the surroundings with the sensors and detectors in hand. Signals are separately used by users for their intended purposes and are exclusive to others.

(2) Seamless handover between navigation methods

While a user moves, the environment he/she is in changes, and the primary navigation method will change accordingly. So same is true when a user's location changes. In these situations, multi-source fusion technology should guarantee the smooth handover between different navigation methods so that there is continuity in this user's location information.

When a user enters an indoor environment from outdoors, the navigation and positioning needs cannot no longer be met by GNSS, as signals attenuate indoors. Therefore, the major navigation and positioning method changes from GNSS to indoor positioning. Multi-source fusion technology must ensure that such transition is seamless so that continuous navigation is delivered reliably and without interruptions or sudden and significant errors.

(3) Seamless fusion of navigation and positioning data

In the same setting there are a variety of navigation and positioning methods available, each with its pros and cons. Therefore, these methods can be combined to achieve the best performance. The key to seamless integration of navigation and positioning data lies in choosing the most appropriate method based on its characteristics and the environment, adjusting the weight of individual methods in the integrated approach so that the advantages of each are fully utilized.

Seen from source data, seamless fusion can be further divided into seamless fusion for measurement domain and seamless fusion for position domain. The former refers to fusion of measurements calculated by multiple methods to delivery position information. An example is GNSS/INS tight coupling. Seamless fusion for position domain mainly integrates positioning estimates by different methods to improve positioning performance.

Seen from how fusion is achieved, seamless fusion has two subcategories: network-side and terminal-side fusion. Network-side fusion involves collecting and fusion of positioning data in information processing center before sending accurate position information to users. Terminal-side fusion is fulfilled through user terminals which achieve fusion of information from multiple sources so as to obtain more precise information about their own positions.

71.3.2 The Purpose of Multi-Source Fusion

The primary purpose of multi-source fusion positioning is to augment GNSS performance in areas including accuracy, continuity, integrity and operability.

Accuracy: A match between the location delivered by the system real-time and the user's actual location.

Continuity: The system's ability in continuously delivering services which meet the established performance requirements under normal operating mode.

Integrity: The system's ability to send alarms to users when it is not effective.

Operability: The percentage of time when the system is providing services which meet the established performance requirements under normal operating mode.

Among the metrics above, accuracy, continuity and operability are key to seamless indoor/outdoor positioning. Operability is affected by accuracy and continuity.

Therefore, a key target for seamless indoor/outdoor positioning is seamless handover and improved accuracy and continuity, hence better navigation and positioning services for users.

71.4 Architecture Design of Multisource Fusion System

71.4.1 Rationale for Multi-Source Fusion Positioning

Technical rationale for multi-source fusion positioning is shown in Fig. 71.1.

Information pre-processing is needed before filtering. Information pre-processing involves: evaluation of signal and data quality, space alignment, time synchronization and outlier processing. Then the processed multi-source navigation information is inputted into multi-source fusion filters, which will deliver high-performance navigation and positioning results after information fusion.

In real navigation scenarios, information transmission and reference data can be non-standard and faulty because of external interference, and issues of timing system and interface technology, making navigation information delivered by navigation devices/systems unsuitable for direct use. Therefore, it must be processed before entered into information fusion filters. These operations before fusion are called pre-processing of information.

Major factors affecting the quality of navigation information are shown below:

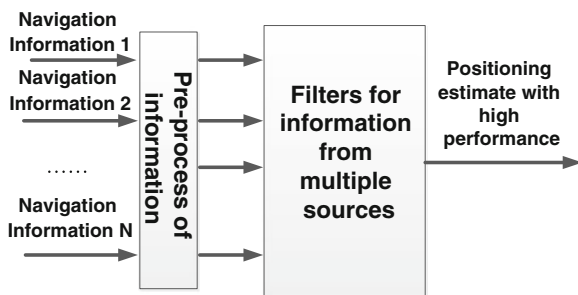
1. Without evaluation and processing, variations in the quality of navigation information sources would hamper the accuracy of multi-source fusion positioning.
2. The coordinate reference system for different navigation devices/systems is not standardized.
3. Navigation and positioning measurements sampled in a certain moment are not for the exact time.
4. Interference of various kinds leads to frequent outliers.

Solutions for the above-mentioned issues are given below.

(1) Evaluation of information quality

In an integrated multi-source system, different measuring approaches can provide location information, operating state and corresponding confidence coefficient; the last two can be used for the evaluation of information quality. When the confidence coefficient fall short of specific requirements or when the operating state

Fig. 71.1 Rationale for multi-source fusion positioning



is abnormal, the corresponding information will be automatically excluded so that the accuracy of multi-source positioning will not be “polluted”. This exclusion operation is called evaluation and processing of information quality.

(2) Spatial alignment

A coordinate system is the chosen benchmark to describe the location and patterns of motion of an object. In a multi-sensor fusion navigation system, measurements for the same physical quantity as described by different coordinate systems must be registered within a single coordinate system so as to shed light on the characteristics and patterns of motion. Moreover, measuring centers for different navigation sources differs and therefore, there is a need to align them to the same measurement point, to achieve consistency of measuring positions.

(3) Information synchronization

An inevitable issue to be addressed during data processing for multi-source fusion is the fact that sampling of time dimensions is out-of-sync due to differences in information sources. It would lead to latency in output seriously affect navigation accuracy if not addressed properly.

Information synchronization of time dimensions can be classified into two levels: the first is consistency of time reference for navigation information from different sources. After the first level has been achieved, the next level is consistency in sampling time.

(4) Outliers handling

Engineering practices show that the combined effect of multiple chance factors result in 1–2 %, or as high as 10–20 % of data points in the measured data set that represent significant variations from the targeted truth value. That is true even for high-precision devices. These variations are referred to as outliers in the field of engineering data processing. Systems that adopt Kalman filters can identify outliers during filtering through predicating the residue. Innovation is defined as: $\varepsilon(k) = Z(k) - H(k)X(k|k - 1)$, And identification calculation is done through

$$|\varepsilon(k)| \leq r \sqrt{(H(k)P(k|k - 1)H^T(k) - R(k))_{i,i}} \quad (71.1)$$

In this equation, r is a coefficient, usually taken as 3 or 4, $H(k)P(k|k - 1)H^T(k)$, represents the variance matrix of one-step-ahead prediction vector, $H(k)$ represents ranging matrix, $X(k)$ represents the state, $P(k|k - 1)$ represents predicated covariance matrix, $R(k)$ represents the covariance of the observation noise. If the equation is true, no outliers are detected in the observations; otherwise there exist variations.

If component i of Z_k is detected by the Kalman filter system as an outlier, elements in the same row as Z_i in the gain matrix are set as zero; therefore the effect of the outlier is eliminated. In such situations, only time update is used in the estimation of the state parameters of the system. If outliers occur continuously, error level for state estimation will be increased because of the unavailability of measured

values. In such situations, fitting is needed for some outliers, namely using information from the limited time before the current moment to fit the data. For instance, the smoothed value of the innovation sequence for discrete times 1 to m is used to replace the innovation for time k.

$$\bar{\varepsilon}(k) = \frac{1}{m} \sum_{i=1}^m \varepsilon(k - i) \tag{71.2}$$

71.4.2 Fusion Methods for Information from Multiple Sources

The architecture of fusion for positioning information from multiple sources is shown in Fig. 71.2.

Kalman filters adopted by multi-source fusion navigation systems are either centralized or decentralized (Figures 71.3 and 71.4).

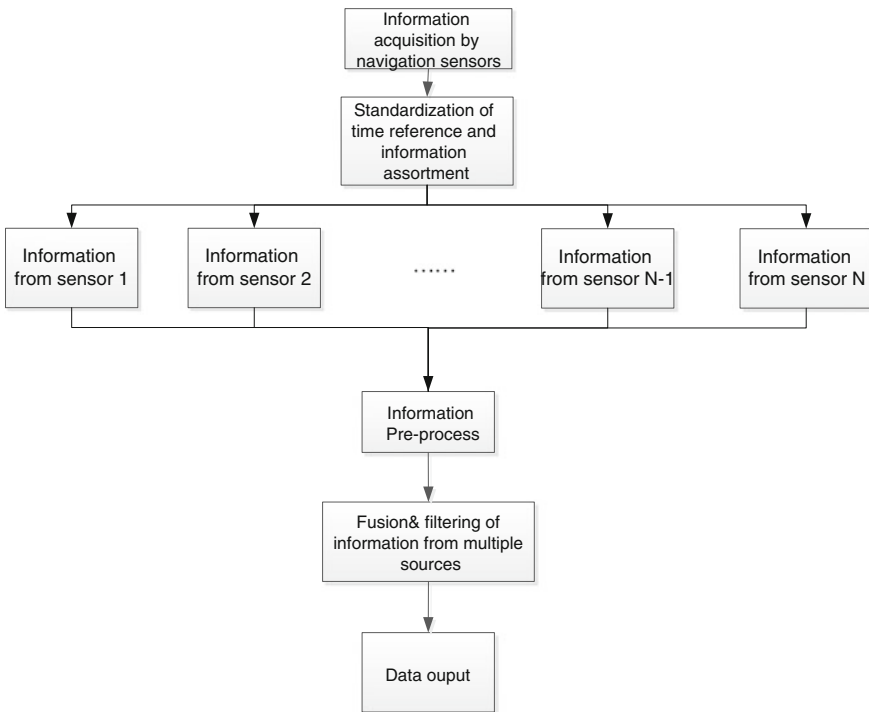


Fig. 71.2 Architecture for multi-source fusion positioning

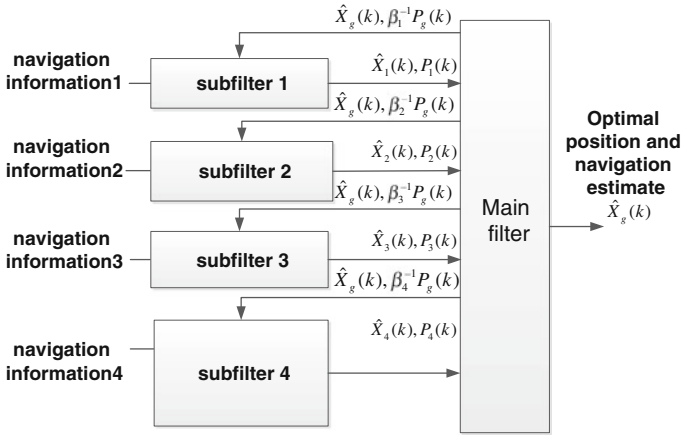


Fig. 71.3 Overall system structure for decentralized filters for multi-sensor fusion

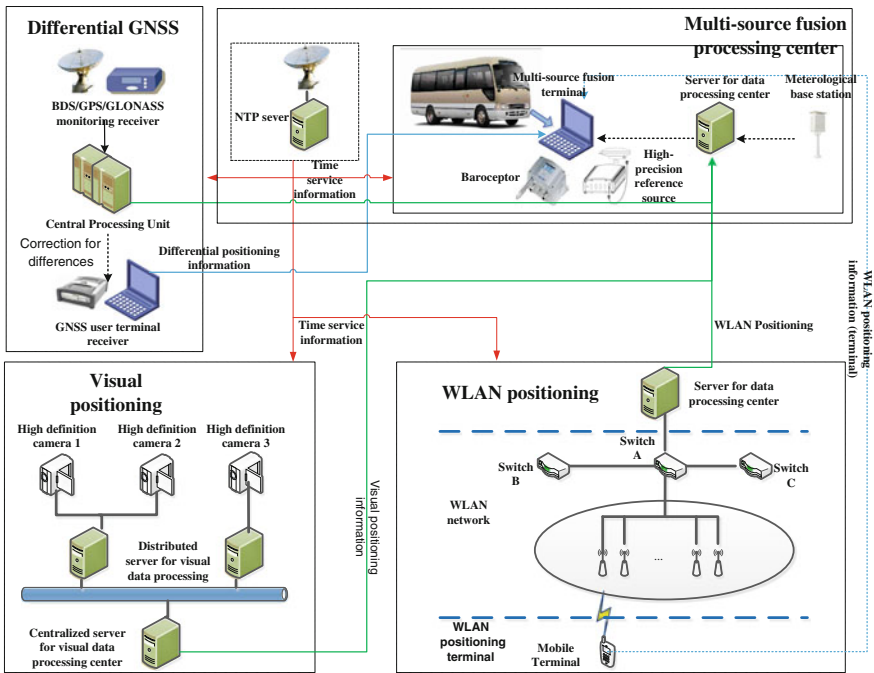


Fig. 71.4 Connection diagram for test equipment

Decentralized Kalman filters for multi-source information fusion are much more robust to errors than centralized ones. Their advantages are listed below:

1. Because their fusion cycle are longer than that of sub filters, there is sufficient time for gradient errors to develop to the level which can be detected by the main filter.
2. Sub filters' states are estimated separately and are not affected by faults in other information sources within the subtitles' cycle. They will only be affected after a long fusion cycle.
3. When faults in a measurement method has been detected and excluded, observations from other sub filters are still there (as long as no resetting has been made) which can lead to a global estimate through simple fusion algorithm. Therefore, decentralized Kalman filters are robust to errors.

For reasons listed above, decentralized Kalman filters are chosen for multi-source information fusion.

The structure for Kalman-based decentralized filters for multi-source fusion is shown above. It is a non-reset one (resetting in decentralized filters would cause cross-contamination of sub filters, resulting in poor robustness to errors.)

It is worth noting that though this filter design is intended for location domain-based information fusion, the overall structure can still be applied to measurement domain. Designs for sub filters and the main filter are discussed in the ensuing part.

(1) Design of sub filters

The main filter uses position domain information from different navigation sensors, while measurements provided by each sub filters differ with different weights, therefore, the state equation and measurement equation for each sub filter should be different. This paper takes differential GPS, passive visual positioning, fingerprinting (WLAN) and positioning based on atmospheric pressure as navigation sources. Sub filter design for each is elaborated in the ensuing passages.

(a) Modeling for sub filters used in GPS

Differential relative positioning can be used for GPS receivers to obtain highly accurate positioning estimates; moreover, estimation of speed can be made with high accuracy via Doppler observations. Therefore, the filtering model can be:

$$\left. \begin{aligned} X_{GNSS}(k) &= \Phi_{GNSS}(k, k-1)X_{GNSS}(k-1) + W_{GNSS}(k) \\ Z_{GNSS}(k) &= H_{GNSS}(k)X_{GNSS}(k) + V_{GNSS}(k) \end{aligned} \right\} \quad (71.3)$$

In the equation, state vector and observation vector are taken respectively as:

$$X_{GNSS} = [e \quad n \quad u \quad V \quad H \quad a \quad \omega]^T \quad (71.4)$$

$$Z_{GNSS} = [e_z \quad n_z \quad u_z \quad V_z]^T \quad (71.5)$$

The position of local coordinate system is represented by e , n and u . Then the following matrices are specified: V , speed; H , heading; a , linear acceleration ω , angular velocity; $W_{GNSS}(k)$ the process noise; and $V_{GNSS}(k)$, the observation noise. The corresponding renewal equation is:

$$\left. \begin{aligned} \dot{e} &= V \sin H + W_1 \\ \dot{n} &= V \cos H + W_2 \\ \dot{u} &= W_3 \\ \dot{V} &= a + W_4 \\ \dot{H} &= \omega + W_5 \\ \dot{a} &= W_6 \\ \dot{\omega} &= W_7 \end{aligned} \right\} \quad (71.6)$$

The renewal equation for observation is:

$$\left. \begin{aligned} e_Z &= e + V_1 \\ n_Z &= n + V_2 \\ u_Z &= u + V_3 \\ V_Z &= V + V_4 \end{aligned} \right\} \quad (71.7)$$

In the equation above, R is the radius of the Earth. The filtering model is obtained through discretization of the state and observation renewal equations shown above. Because the state vector is nonlinear, it can be integrated with a extended Kalman filter for optimal filtering.

(b) Modeling for sub filters used in passive visual positioning

Sub filters used in passive visual positioning are designed in a image coordinate through the location-speed model. State vectors chosen are:

$$\mathbf{X}_{VISION} = [x_p \quad y_p \quad V_{xp} \quad V_{yp}]^T \quad (71.8)$$

In the equation above, x_p and y_p represents the coordinate of the carrier in the image coordinate system. V_{xp} and V_{yp} are speeds in the corresponding direction. So the resulting state model is:

$$\left. \begin{aligned} \mathbf{X}_{VISION}(k) &= \Phi_{VISION}(k, k-1)\mathbf{X}_{VISION}(k-1) + \mathbf{W}_{VISION}(k) \\ \mathbf{Z}_{VISION}(k) &= \mathbf{H}_{VISION}(k)\mathbf{X}_{VISION}(k) + \mathbf{V}_{VISION}(k) \end{aligned} \right\} \quad (71.9)$$

In the equation above, $W_{VISION}(k)$ represents the process noise while $V_{VISION}(k)$ the observation noise.

Because the carrier's position (x_{po}, y_{po}) and linear velocity v_{po} are available, an observation model can be established:

$$Z_{VISION} = [x_{po} \quad y_{po} \quad v_{po}]^T \quad (71.10)$$

$$\left. \begin{aligned} x_{po} &= x_p + v_1 \\ y_{po} &= y_p + v_2 \\ v_{po} &= \sqrt{V_{xp}^2 + V_{yp}^2} + v_3 \end{aligned} \right\} \quad (71.11)$$

Subfiltering can be completed based on Eqs. (71.10) and (71.11).

(c) **Modeling for subfilters used in fingerprinting (WLAN)**

The state vector in WLAN positioning is taken as:

$$\mathbf{X}_{WLAN} = [x_{we} \quad y_{wn} \quad V_{ew} \quad V_{nw}]^T \quad (71.12)$$

Taking positions in the east and north as indicated by WLAN positioning as observation vectors, and the corresponding observation equation is:

$$\left. \begin{aligned} \mathbf{X}_{WLAN}(k) &= \Phi_{WLAN}(k, k-1)\mathbf{X}_{WLAN}(k-1) + \mathbf{W}_{WLAN}(k) \\ Z_{WLAN}(k) &= [x_{we} \quad y_{wn}]^T = \mathbf{H}_{WLAN}(k)\mathbf{X}_{WLAN}(k) + \mathbf{V}_{WLAN}(k) \end{aligned} \right\} \quad (71.13)$$

In the equation

$$\mathbf{H}_{WLAN}(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (71.14)$$

$W_{WLAN}(k)$ is specified as the process noise, and $V_{WLAN}(k)$ the observation noise.

(d) **Modeling for subfilters used in positioning based on atmospheric pressure**

Since Baroreceptors can only provide altitudinal information, the output data is relatively simple. Therefore, the method of least squares can be adopted in output data filtering. The corresponding observation model is:

$$\Delta h_{bar} = \Delta h + W_{bar} \quad (71.15)$$

(2) **Design of the main filter**

Execute one time update step for each subfilters mentioned before through the equations below:

$$\begin{aligned} \hat{X}_i(k, k-1) &= \Phi(k, k-1)\hat{X}_i(k-1) \\ P_i(k, k-1) &= \Phi(k, k-1)P_i(k-1)\Phi^T(k, k-1) + Q_i(k-1) \end{aligned} \tag{71.16}$$

In the equation, $i = 1, 2, 3, 4$, respectively corresponding to subfilters for GNSS, visual positioning, WLAN positioning and positioning based on atmospheric pressure. Matrices are specified as follows: $P_i(k, k-1)$ the one-step-ahead prediction of the covariance matrix of the state estimate for subfilter i ; $P_i(k, k-1)$, the covariance matrix of the state estimate for subfilter i ; and $Q_i(k-1)$, the covariance matrix of the process noise.

Then, the coordinates of each methods are transformed to a unified geodetic coordinate XYZ systems. Herein, WLAN results and Baroceptor results form a 3D positioning result.

Fusion in the main filter is calculated:

$$\left. \begin{aligned} X(k) &= \Phi(k, k-1)X(k-1) + W(k) \\ Z(k) &= H(k)X(k) + V(k) \end{aligned} \right\} \tag{71.17}$$

The measured results are formed by GNSS positioning results, visual positioning results and WLAN and baroceptor based positioning results.

The states are location, velocity and acceleration of each results

$$\left. \begin{aligned} x(k) &= x(k-1) + v(k-1)t + 1/2a(k-1)t^2 \\ v(k) &= a(k-1)t \\ a(k) &= a(k-1) \end{aligned} \right\} \tag{71.18}$$

Fused results are showed below:

$$\begin{aligned} P_g^{-1}(k) &= \sum_{i=1}^3 P_i^{-1}(k) \\ \hat{X}_g(k) &= P_g(k) \sum_{i=1}^3 P_i^{-1}(k)\hat{X}_i(k) \end{aligned} \tag{71.19}$$

At last, the global filtering estimates $P_g(k)$ and $X_g(k)$ execute information distribution based on the following equations:

$$\begin{aligned} P_i^{-1}(k) &= \beta_i P_g^{-1}(k) \\ \hat{X}_i(k) &= \hat{X}_g(k) \end{aligned} \tag{71.20}$$

71.5 Testing and Analysis

Based on the requirements of the preliminary test, the new technology base of Chinese Academy of Sciences was chosen as a test ground where equipment including stations for differential GNSS corrections, WLAN signal nodes, devices for passive visual positioning, devices for correcting differences in atmospheric pressure, and communication devices was in place. Terminals tested include GNSS, WLAN and atmospheric pressure testing modules. They receive data such as corrections of differential GNSS, WLAN fingerprinting data, and atmospheric pressure measurements and obtain estimates of differential GNSS and WLAN positioning and atmospheric pressure-derived altitudes. Fusion of these estimates results in terminal-side estimation of the position.

Diagram for test environment is presented in Fig. 71.5.

Figure 71.6a, b are positioning track comparisons of actual measurements of single method positioning and fusion method positioning respectively, herein (a) shows results of outdoor scenario with (b) of indoor scenario. In the figure, the deep blue line represents fusion positioning results, the deep red line denotes high-precision reference, and in outdoor environments, we can see the two lines are almost in alignment, prevailing over other single method positioning results. Figure 71.6 shows that seamless handover between indoor/outdoor positioning within the tested area can be realized. Actual measurements reveal that seamless handover between indoor/outdoor positioning which ensures continuous positioning with navigation and positioning frequency of 1 Hz within the test area is possible using the architecture and algorithm of the multi-source fusion system mentioned before. Figure 71.6c shows comparisons of fusion positioning and differential positioning, herein, the blue line represents differential result, and the red

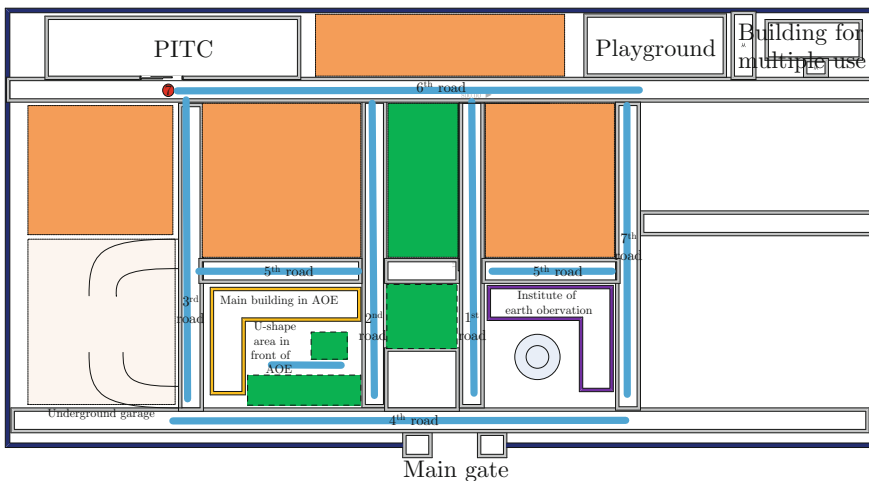


Fig. 71.5 Diagram for test environment

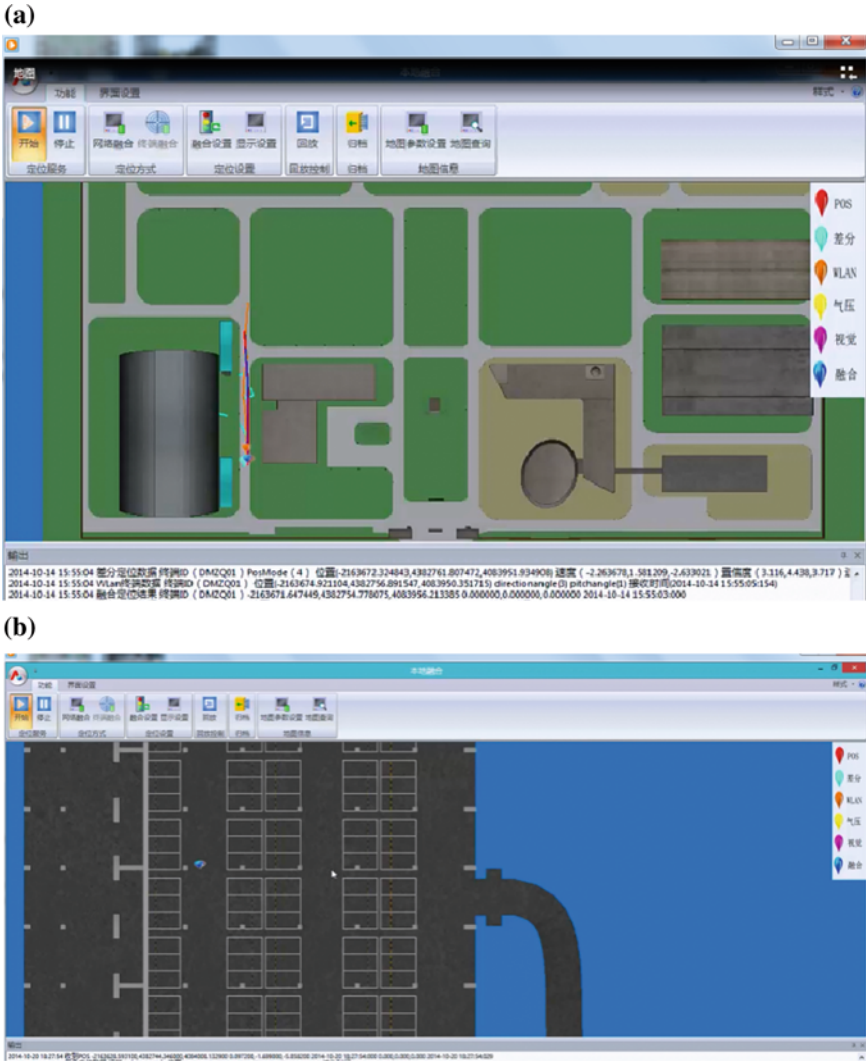


Fig. 71.6 Results for indoor/outdoor positioning. **a** Results for outdoor positioning. **b** Results for indoor positioning. **c** The fusion positioning result (the red one) and the GNSS positioning result (the blue one)

one represents the other result. From Fig. 71.6, we can see fusion positioning precision is obviously better than GNSS local differential precision, and guarantees continuous positioning even when GNSS data drifts apparently in urban valley.

The vehicle was running for 1 h within the test area with positioning results during this process gathered. The calculated errors for network-side and terminal-side positioning are presented separately in Fig. 71.7.



Fig. 71.6 (continued)

It must be pointed out that reference data is not available for underground garage. (The test adopted high-precision GNSS/INS integrated device for reference, which can not be used in underground garage because of drifting.) Therefore, qualitative analysis mainly focuses on the accuracy of surface positioning. Accuracy of positioning in the underground garage is analyzed through estimation.

Figure 71.7 is positioning error analysis diagram of fusion positioning, where red line is error standard line corresponding to 1σ (66.7 %) probability, and it shows that whether it is network-side or terminal-side positioning, multi-source fusion positioning is more accurate than any single positioning method, with positioning accuracy better than 1 m (1σ).

Indoor positioning is usually fulfilled through WLAN and baroreceptor-derived positioning. Its accuracy is affected by that of the WLAN and baroreceptor-derived positioning. (WLAN is responsible for accuracy of two-dimensional [horizontal] position estimation while baroreceptors for one-dimensional [altitudinal]). Testing of fixed points show that baroreceptor-derived positioning within the test area has a accuracy performance of better than 0.4 m, and WLAN positioning better than 3 m. Therefore the accuracy level for dynamic indoor positioning is about 3 m (1σ).

Moreover, comparison of the continuity performances of different positioning methods show that multi-source fusion positioning can improve continuity: it is 40 % better than differential GNSS, and 10 % better than WLAN positioning. This paper proposes an architecture and filtering algorithm for the multi-source fusion based system. Seamless indoor/outdoor positioning through the integration of

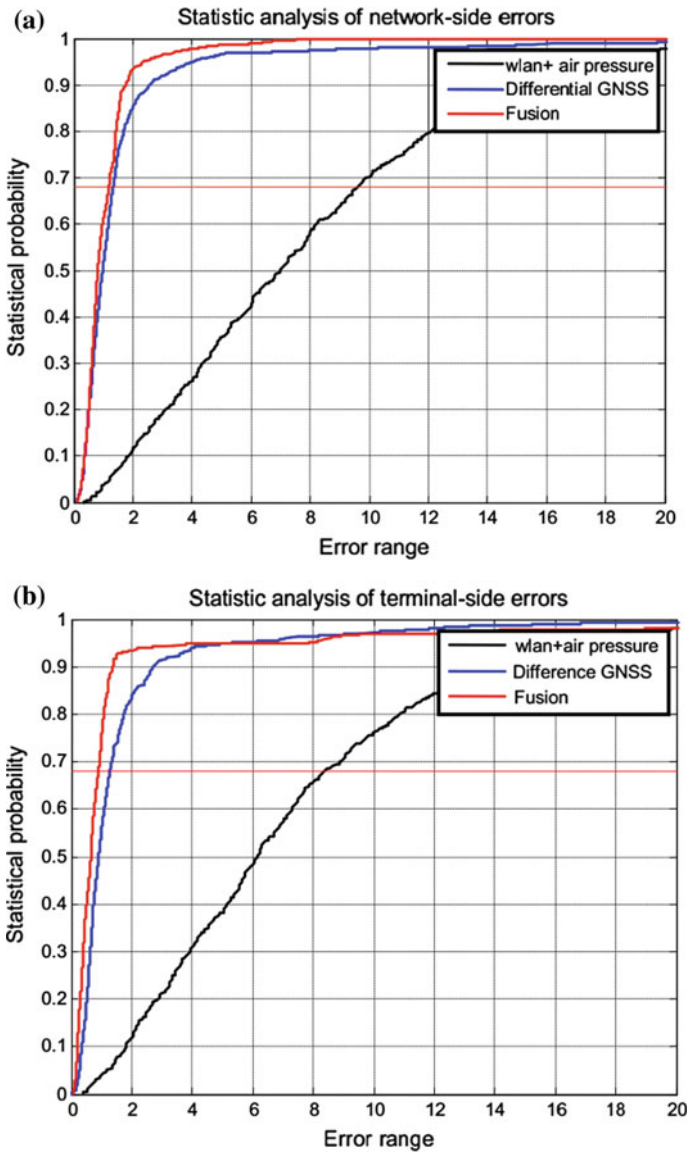


Fig. 71.7 Accuracy analysis for fusion positioning. **a** Error analysis for network-side positioning. **b** Error analysis for terminal-side positioning

multiple positioning methods was tested. Results show that this technology effectively improves the accuracy and continuity of GNSS and can meet users' demand for seamless indoor/outdoor positioning. Multi-source fusion positioning points to a new approach for seamless indoor/outdoor positioning, and is a case of the

application of multi-source fusion in navigation and positioning, hence providing a reference for the development of all-source navigation technology, opportunity navigation technology and PNT technology.

71.6 Conclusion

This paper analyses basic characteristics of navigation signal and communication signal, and proposes a novel signal system bearing basic features of communication signal, aiming at realizing deep fusion in signal layer. In this paper, the new signal's correlation function, power spectrum density, RMS bandwidth and positioning accuracy are studied, followed by comparative analysis of the new signal and BPSK modulated C/A code signal and BOC modulated BOC (4,1) signal, with the conclusion that BCC signal has better of navigation and positioning performance. Moreover, this study also puts forward signal synchronization algorithm based on signal features, simulates signal performance and tests and verifies key algorithm. The result indicates that single-carrier BCC signal's ranging accuracy is 6.06 m, and positioning accuracy is 10.8 m. The ranging and positioning accuracy will be better in multi-carrier conditions, which will be sufficient for users' basic positioning requirements. The analysis of communication signals confirms that the signal is able to integrate with existing communication signals, which is worthy of further in-depth study.

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