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Article

Multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filter

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Abstract: With the widespread application of Global Navigation Satellite System (GNSS) in the fields of positioning and navigation, traditional single frequency and single system positioning methods are gradually unable to meet the requirements of high accuracy and high reliability. Especially in complex and dynamic environments, GNSS signals are affected by multipath effects, occlusion, and interference, resulting in a significant decrease in positioning accuracy. Therefore, it is particularly important to develop a multi-frequency and multi-system GNSS positioning data fusion algorithm. This article used Kalman filtering technology and combined the data characteristics of multi-frequency and multi-system GNSS signals to study a new positioning data fusion algorithm. By comprehensively processing different GNSS systems and frequency signals, the positioning accuracy and anti-interference ability were significantly improved. The experimental results showed that the algorithm studied improved the average positioning accuracy by more than 6.23% in complex environments compared to traditional methods, and also exhibited good adaptability and stability under dynamic conditions. Fully utilizing the advantages of multi-frequency signals and combining advanced data fusion technology is an effective way to improve GNSS positioning performance, providing new ideas and methods for future intelligent navigation applications.

Keywords: global navigation satellite system; Kalman filter; data fusion; multi-frequency multi-system

1. Introduction

Global Navigation Satellite Systems (GNSS) play a crucial role in the fields of positioning, navigation, and time synchronization in modern society. However, traditional positioning methods have certain limitations in terms of positioning accuracy, stability, and anti-interference ability. The main contribution of this study is the proposal of a multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filtering. This algorithm significantly improves positioning accuracy and system reliability by effectively fusing data from different frequency bands and systems.

The organizational structure of this article is as follows: firstly, the basic principles of GNSS positioning and the main challenges it faces are introduced; secondly, the proposed Kalman filtering algorithm and its application in multi-frequency and multi-system data fusion are described in detail, including the observation model and data preprocessing process; next, the experimental design and its results are presented, and the performance of traditional methods and new algorithms in terms of positioning accuracy and stability is compared; finally, the significance of the results in practical applications is discussed, and future research directions are proposed.

The problem to be solved in this article is how to improve positioning accuracy and anti-interference ability by integrating multi-frequency and multi-system GNSS data in dynamic environments. The innovation lies in the use of Kalman filtering technology to process and fuse observation data from different GNSS systems, thereby overcoming the limitations of traditional methods. The technical solution includes modeling observation noise and system errors, using weighted averaging for data preprocessing, and using Kalman filtering for state estimation and data fusion. This method not only improves positioning accuracy, but also enhances the stability and reliability of the system under various environmental conditions, providing new ideas and methods for the future development of navigation technology.

2. Related work

There have been many studies on location data fusion recently. Cheng [1] designed a speed measurement method that combined Doppler radar and inertial sensors, effectively improving the accuracy of vehicle speed measurement and positioning in pipeline corridors, and providing reliable guarantees for the safe operation of pipeline logistics systems. Based on Bayesian filtering and swarm intelligence theory, Bai [2] proposed a wireless aviation search and rescue data fusion positioning method based on robust artificial fish swarm particle filtering. Zhao [3] proposed an improved single star direct positioning method for real valued space-time subspace data fusion, which achieved direct positioning of multiple radiation sources by a single star under the condition of known radiation source elevation. Acar [4] proposed an indoor positioning scheme based on IMU (Inertial Measurement Unit) and Bluetooth data fusion, aiming to achieve sub meter level positioning accuracy. Ghazal [5] explored a machine learning architecture based on data fusion to improve the performance of intrusion detection systems, emphasizing the importance of fusing different types of data (such as network traffic, user behavior, etc.) to enhance detection accuracy. These studies did not fully consider the noise, missing values, and diversity of sensor data, which affected the final fusion effect.

There are also many studies on the application of Kalman filtering. Xu [6] was based on the Kalman filter method and used a dual-mode positioning module to fuse the positioning data of the Beidou system and the global positioning system, greatly improving the positioning accuracy and reducing errors. Wang [7] proposed a visual inertial adaptive fusion method based on variational Bayesian inference in the error state Kalman filtering framework. This method had high accuracy and robustness, and achieved fast and high-precision tracking of targets. Bakhshi Ostadkalayeh [8] studied the application of deep learning models based on LSTM (Long Short-Term Memory) Network in traffic prediction, and combined it with Kalman filtering technology for performance improvement. Ghansah [9] reviewed the application of nonlinear Kalman filtering in target tracking, reviewed different nonlinear filtering techniques, and explored their effectiveness in dynamic environments. Winiwarter [10] applied Kalman filtering in its research to analyze the full four-dimensional changes of terrain point cloud time series. Kalman filtering can not only handle the noise of time series data, but also extract key change information, providing an effective method for surface dynamic monitoring. In dynamic environments, the system model changes rapidly, and the fixed model of Kalman filtering cannot adapt quickly to new changes, resulting in a decrease in the performance of the filter.

3. Methods

3.1. System state modeling

In GNSS positioning, the accuracy of observation values directly affects the accuracy and reliability of positioning results. Among them, the accuracy of observation is determined by both observation noise and systematic error. Therefore, in order to achieve high positioning accuracy, it is necessary to filter the GNSS observation data to meet certain accuracy requirements. For the multi-frequency and multi-system GNSS positioning data fusion algorithm, its state model is described as follows [11]:

$$Q = C\theta + TI \tag{1}$$

Among them, θ is the system state vector; I is the random noise; T is the influence matrix. At the same time, Kalman filtering technology is used to update the observation vectors, thereby further improving the positioning accuracy of the entire system. It can be seen that in this model, the system error is jointly determined by errors such as receiver clock bias, multipath effects, and multipath effects; observation noise is caused by random errors and tropospheric delays generated during the propagation of satellite signals. When the receiver clock bias is small, the system error mainly comes from the receiver clock bias and tropospheric delay, and gradually increases with the increase of differences between multiple systems; when the receiver clock bias is large, it comes from the differences between multiple systems. It can be seen that in this model, multiple system errors and multipath effects are the main sources of error affecting positioning accuracy. Meanwhile, when there are significant differences between multiple systems, it leads to an increase in system errors. Due to the significant differences between multiple systems, the errors in receiver clock bias and tropospheric delay further increase. Among them, in order to process the observation noise, corresponding observation equations need to be established [12]:

$$(p, q) = A(x, y) + B(i, j)\varepsilon \tag{2}$$

Among them, p and q are receiver clock errors; x and y are tropospheric delays; ε is random noise. In the multi-frequency and multi-system GNSS positioning data fusion algorithm, the main sources of observation noise are: the first is random errors generated during satellite signal propagation; the second is the observation error caused by tropospheric delay; the third is the system error caused by receiver clock bias. In order to filter observation noise, the least squares estimation method is usually used. The steps are as follows: firstly, the clock bias and inter epoch bias of the satellite are calculated based on the ephemeris file, thereby obtaining the carrier phase and pseudorange values of the satellite in each system; secondly, pseudorange observations are used for positioning, and the pseudorange result is multiplied by a certain coefficient and subtracted from the satellite clock bias to obtain the satellite clock bias given in the ephemeris; thirdly, the carrier phase observation value is used for positioning calculation, and the pseudo range result is multiplied by a certain coefficient and subtracted from the satellite clock difference to obtain the carrier phase observation value; fourthly, the carrier phase observation values are used for positioning calculation.

There are mainly two traditional single frequency receiver calculation models: one is the pseudorange differential model based on pseudorange and phase observations, and the other is the phase differential model based on carrier phase observations. These two methods each have their own advantages and disadvantages, but the phase difference model used in this article is based on carrier phase observations. In practical applications, it is impossible for a single receiver to simultaneously observe satellite signals on all frequencies. Therefore, the solution method of “pseudorange difference+carrier phase difference” is adopted. In the pseudorange differential model, it is further divided into carrier phase differential observations and carrier phase observations. This article mainly studies the pseudo range differential model based on carrier phase observations. At present, a differential observation calculation method for carrier phase observations is implemented on single frequency receivers. Although this method effectively solves the problem of multi-system fusion, the calculation process is relatively complex and the solution time is also long.

3.2. Kalman filter design

The Kalman filter algorithm is an optimal linear system used for estimating state equations and measurement equations. The implementation process of the multi-frequency and multi-system GNSS positioning data fusion algorithm is divided into the following three stages: first, multiple GNSS systems and frequency data are preprocessed; then, the observation data is filtered and estimated; finally, the observation data is fused. The first step is to preprocess multiple GNSS systems and frequency signals, mainly including estimating various ionospheric delays, estimating multipath effects, and detecting multi-carrier phases. In the above process, it is necessary to make reasonable estimates of various ionospheric delays and multi-carrier phases, and these observational data contain a large amount of noise. If these noises cannot be accurately removed, it seriously affects the accuracy and reliability of the filtered estimation values. Therefore, in the preprocessing process, it is necessary to estimate various ionospheric delays and determine corresponding weights and thresholds based on satellite position, observation noise, and other information. The second step is to fuse the observation data with the fused observation data. For multi-carrier phase observations, they are all sent by satellites and reflected, refracted, or diffracted by the ionosphere before reaching the receiver and being received by the receiver. For multi-carrier phase observations, their observations are usually obtained by measuring noise and model errors. When GNSS signals pass through the ionosphere, errors and model errors are generated, which directly affect navigation and positioning accuracy. Therefore, it is necessary to estimate and correct measurement noise and model errors. When estimating these measurement noises and model errors, multiple types of measurement noises and model errors need to be considered. The third step is to fuse the navigation and positioning data. After the positioning data is processed as described above, the navigation positioning accuracy is significantly improved. However, in practical applications, due to limitations such as environmental and equipment conditions, the impact of measurement noise and model errors cannot be completely eliminated. Therefore, it is necessary to fuse navigation and positioning data to further improve its positioning accuracy and reliability. In addition, it is necessary to filter and estimate navigation data to eliminate or suppress the effects of various measurement noise, model errors, and other factors.

In GNSS data preprocessing, the weighted average method is generally used. The so-called weighted average refers to using different weights for data collected by multiple GNSS systems based on different observation values to improve data quality. Usually, when performing weighted averaging, two factors are mainly considered: firstly, for the same satellite system, due to their independent observation data, the data obtained by weighted averaging has the same accuracy as the original observation values; secondly, for different satellite systems, due to the different characteristics of the data collected, the weighted average of the data obtained from them has different accuracy compared to the original observation values. Due to the fact that multi-frequency and multi-system GNSS positioning data typically contains observations of multiple frequencies and types, there are often issues with weighted averaging where observations of different frequencies or types are assigned the same weight and threshold conditions, resulting in the same or even opposite weighted results. Therefore, it is necessary to segment and process observations of various frequencies and types reasonably. The specific method is to divide the observations collected by multiple GNSS systems according to their frequencies, and divide them into different frequency points based on their frequency location and surrounding environment information. Assigning different weights and threshold conditions to these frequency points is to better ensure that the weighted results have the same or opposite accuracy when weighted averaging different types of observations.

In order to better ensure the reasonable segmentation and processing of various types of observation values during navigation data preprocessing, it is necessary to reasonably divide and allocate the different weights of each type of observation value. Among them, for the same satellite system, due to the same or opposite accuracy levels of the collected data, the results obtained by assigning different weights are the same or opposite. The basic idea of filter estimation is to use the information contained in the observed data to convert it into a new state variable, and then estimate the system state through this state variable. In practical applications, due to limitations such as environmental and equipment conditions, it is often not possible to directly use all observed data for filtering estimation. It is necessary to perform prior processing on some data to improve the accuracy of filtering estimation values. Normally, prior data includes satellite position, satellite orbit, ephemeris parameters, and observation noise. Firstly, the relevant satellite positions and ephemeris parameter information are used as prior information, and then the observation noise information is used as prior information. Due to the fact that prior information accurately reflects the errors and noise contained in the observed data, it can be used as the main basis for filtering estimation. After fusing prior information and filtered estimation values, the positioning accuracy is further improved. For multi-frequency and multi-system GNSS positioning, the system state equation is usually expressed as [13]:

$$x_t = Fx_{t-1} + Gw_t \tag{3}$$

Among them, F is the state transition matrix, and G is the control matrix. The process of multi-frequency and multi-system GNSS positioning data fusion mainly includes three stages, namely data preprocessing stage, filtering estimation stage, and fusion processing stage. Among them, the data preprocessing stage mainly includes effectively extracting multi-frequency and multi-system GNSS satellite observations, and reasonably preprocessing the observation data; the filtering estimation stage is the effective fusion of observed data and preprocessed data; the fusion processing stage is to effectively process the fused navigation data. In practical applications, the three stages are usually applied separately to different situations to improve navigation and positioning accuracy. For example, in multi-frequency and multi-system GNSS positioning systems, due to signal propagation issues with some satellites, the process of data fusion for multi-frequency and multi-system GNSS positioning is different from that of a single system. Therefore, when performing multi-frequency and multi-system GNSS positioning data fusion, it is necessary to make a reasonable estimation of the satellite signal propagation problem. In addition, due to the differences between multi-carrier phase observations and single carrier phase observations, the fusion process of multi-carrier phase observations and single carrier phase observations needs to consider the differences between them. The process of multi-frequency and multi-system GNSS positioning data fusion is shown in **Figure 1**.

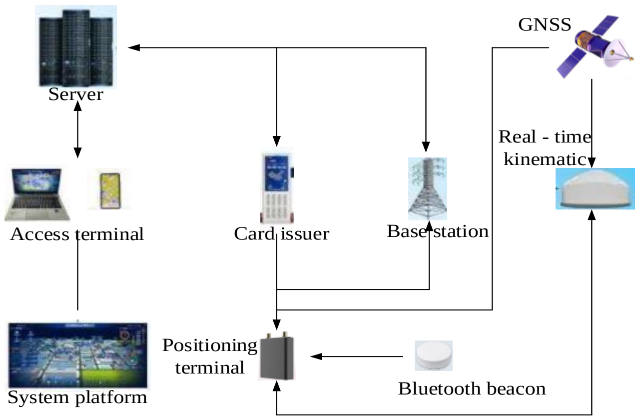

Figure 1. Multi-frequency and multi-system GNSS positioning data fusion process.

Figure 1 includes various elements such as servers, access terminals, system platforms, card issuers, base stations, positioning terminals, Bluetooth beacons, GNSS, and real-time dynamic technology. Firstly, the observation data before fusion is preprocessed. Then, two different types of navigation data are separately filtered and estimated. Finally, the two sets of navigation data are fused. By repeatedly iterating the above steps, a set of high-performance navigation and positioning data is finally obtained. In the process of multi-frequency and multi-system GNSS positioning data fusion, after reasonable preprocessing and filtering estimation, the navigation positioning accuracy is significantly improved.

The performance of the Kalman filter depends on the precise setting of multiple parameters. The selection of the process noise covariance matrix, the measurement noise covariance matrix and the Kalman gain has a decisive influence on the state prediction, response time and positioning accuracy of the system. The adjustment of the process noise covariance matrix directly affects the system's adaptability to noise and filtering performance. Increasing the value of this matrix can reduce the dependence on model prediction and maintain the stability of the filter in a dynamic environment. The measurement noise covariance matrix plays a key role in the weight of the observation value in the state estimation. Through reasonable settings, the signal interference under high noise conditions can be reduced to ensure the positioning accuracy under complex conditions. The setting of the Kalman gain determines the way the system fuses the predicted value and the observed value. When the error is large, increasing the Kalman gain can make the system more sensitive to the observed data, thereby improving the positioning accuracy.

During the experiment, a sensitivity analysis was performed based on the observed data in different environments to observe the impact of parameters on positioning error and system stability, so as to determine the optimal parameter combination. In a high-interference environment, increasing the value of the process noise covariance matrix can effectively reduce the impact of signal reflection and occlusion on positioning accuracy, while in an environment with relatively stable signal strength, reducing the value of the measurement noise covariance matrix can help improve accuracy. In the multi-frequency and multi-system GNSS data fusion application, the best fusion effect can be achieved by gradually adjusting the parameters according to the signal noise characteristics and data uncertainty. The tuning strategy ensures the repeatability of the experiment and the versatility of the algorithm.

4. Signal processing and data fusion

4.1. Multi-frequency signal processing

The processing of multi-frequency signals in the Global Navigation Satellite System (GNSS) involves selecting methods based on the frequency distribution of different satellites and user needs. Real-time signal processing provides prior information for Kalman filtering, which, combined with user location, time, and speed, ensures high-precision positioning. In GNSS data fusion, methods like pseudorange measurement, carrier phase, and differential measurements are employed. Pseudorange measurement, including both carrier phase and pseudorange methods, is the simplest and foundational, requiring less accuracy for faster positioning. The GNSS includes frequency bands for Beidou, GPS, and Galileo systems, with Beidou and GPS offering higher accuracy but a smaller frequency proportion, while Galileo uses mixed frequencies. Therefore, when using the pseudorange method with two different frequencies for pseudorange measurement, its accuracy can be improved by processing them separately in different frequency bands.

For the Beidou system and the Global Positioning System, due to their long observation time and high accuracy, the carrier phase pseudorange measurement method can be directly used. However, due to the small frequency proportion occupied by the Galileo system and the low requirement for observation accuracy under the same conditions, the carrier phase pseudorange measurement method is used for pseudorange measurement. Carrier phase differential measurement is the process of performing carrier phase differential processing on observed data at the receiver or base station to improve measurement accuracy. For methods based on carrier phase difference measurement, it is usually achieved by obtaining carrier phase observations from satellites and receivers, calculating two pseudo range observations and one carrier phase observation, and finally locating based on the difference between the two. According to its basic principles, it can be divided into two types: differential methods based on carrier phase measurement and differential methods based on carrier phase differential measurement. The method based on carrier phase difference measurement requires high information such as satellite position and satellite elevation angle, and is generally used for high-precision positioning. In practical applications, it is necessary to design and select multi-frequency and multi-system GNSS receivers. Taking the Global Positioning System as an example, when performing multi-frequency and multi-system GNSS positioning data fusion, the first step is to select the appropriate navigation frequency. Because the higher the frequency, the stronger the search ability for the ambiguity of the entire cycle, higher accuracy positioning results are correspondingly obtained. Secondly, it is necessary to select appropriate frequency points for real-time processing of multi-frequency signals. Finally, carrier phase differential measurement methods on different frequencies are chosen to improve positioning accuracy. In addition, it is necessary to select appropriate carrier phase observation values for tracking observation values, in order to ensure that the impact of data errors in subsequent data processing and Kalman filtering is minimized [14].

4.2. Data fusion strategy

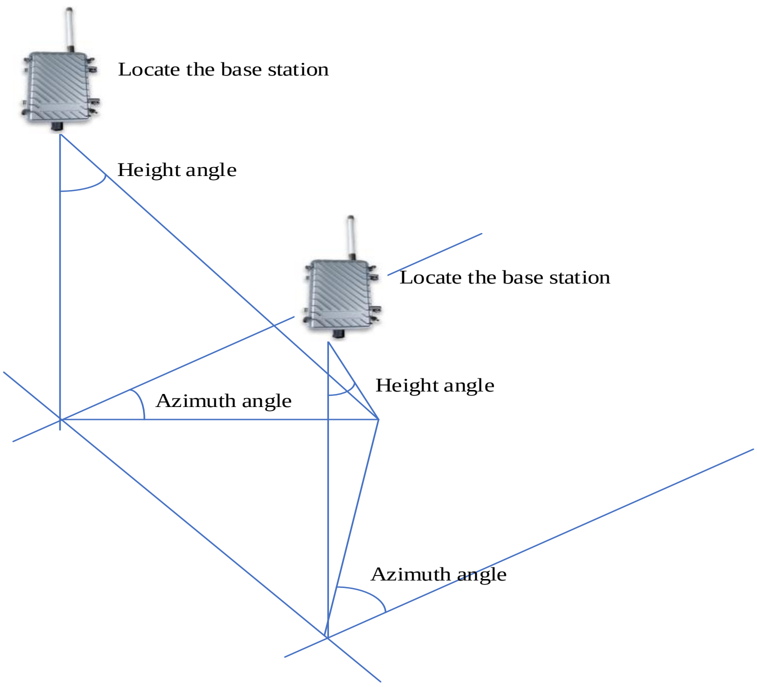

Figure 2. Traditional high-precision positioning methods.

In the data fusion algorithm presented in this article, GNSS signals are divided into three parts for processing. Firstly, traditional high-precision positioning methods such as differential positioning are processed, and then the differential data and satellite clock difference data are used as observation data for Kalman filtering. Finally, the positioning results are subjected to error analysis. In each section, different methods are used to process the data. The traditional high-precision positioning method mainly relies on altitude angle, azimuth angle, and positioning base station, as shown in **Figure 2**.

Unlike traditional methods, advanced high-precision positioning methods first use pseudorange observations to filter and estimate the observed values, obtaining the estimated values and relative errors of the observed values; then, the differential observations are used to filter and estimate the observations, and the corrected observations are obtained through Kalman filtering; finally, the corrected observations are combined with satellite clock bias data as observations, and Kalman filtering is used to estimate the corrected positioning results. By using this method, the positioning accuracy can be effectively improved. Satellite clock bias data contains time and distance information. At different frequencies, there are significant differences in this information. In order to utilize this information for fusion processing, it is necessary to preprocess the clock error data first. The specific steps are as follows: first, Fourier transform is used to convert clock bias data into frequency domain; then, FFT is used to convert the correlation values in the frequency domain into the time domain; finally, the relevant values in the time domain are processed to obtain clock bias data. During the dynamic positioning process, dynamic errors are handled. In dynamic environments, the positioning accuracy decreases due to various interference sources such as airplanes, cars, pedestrians, etc. The principle of differential positioning is to use two adjacent differential observations, where one observation is used to filter the other observation and the other observation is used to correct the filtered result. Therefore, in the process of differential positioning, satellite state estimation and receiver state estimation are separate and have no relationship with each other. Differential positioning is shown in **Figure 3**.

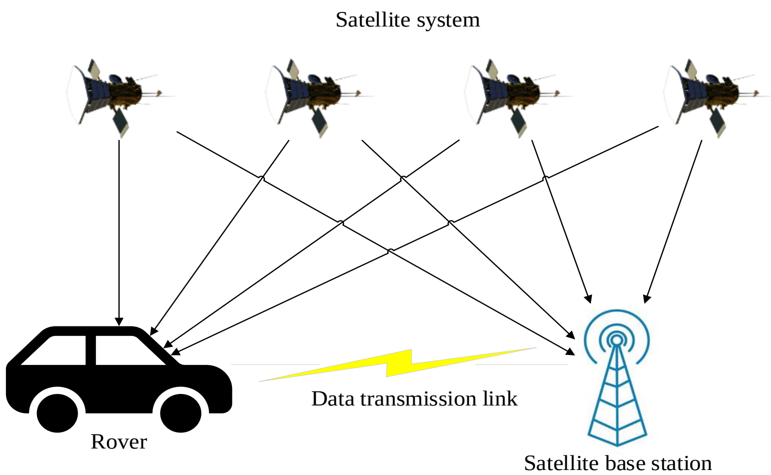

Figure 3. Differential positioning.

In the prediction stage, the observed values are first smoothed. The main smoothing methods include exponential smoothing, least squares, and Gaussian filtering. The exponential smoothing method is used to eliminate gross errors in the observed values, in order to reduce the impact of gross errors in the pseudo range observations; the least squares method is to weight the satellite state and then calculate the corrected observation based on the correlation between the observation values; the Gaussian filtering method estimates the noise present in the observed values and then performs filtering processing. In practical applications, Gaussian filtering is usually chosen for differential localization. The differential positioning results are superior in accuracy to pseudo range and carrier phase observations. However, in dynamic environments, differential positioning cannot obtain accurate results. Specifically, in dynamic environments, there are many uncertain factors in the differential positioning process, such as the influence of dynamic interference sources such as airplanes and cars; secondly, satellite signals and receiver signals are subject to a lot of interference, resulting in differences between pseudorange and carrier phase observations in differential positioning results; thirdly, differential positioning is a continuous process, and there may be errors in the observed values at different times; finally, in dynamic environments, the receiver's state is uncertain due to issues such as interference and unstable signals. Therefore, it is difficult to achieve high-precision positioning in dynamic environments. By preprocessing, frequency domain conversion, time domain conversion, and Kalman filtering of satellite clock bias data, the following observation equation is obtained [15]:

$$z_t = Hx_t + v_t \tag{4}$$

Among them, H is the observation matrix, and v_t is the observation vector. Assuming there are n observed values, the Kalman filter equation is as follows:

$$K = Ph_k(h_kPh_t + R_k)^{-1} \tag{5}$$

Among them, R_k represents the covariance of observed noise. Due to the differences in positioning signals between different systems, the observation values of different systems should be processed separately when analyzing the positioning results for errors. The final positioning result is estimated using Kalman filtering to obtain a corrected positioning result. In the process of data fusion, the first step is to filter and estimate each observation value. By comparing the difference between each estimated value and the true value, whether the current filtering algorithm is effective is determined. If it is effective, filtering is continued; if it is not effective, the observed value is compared with the true value. If the difference between the two is greater than a certain threshold, the current filtering algorithm is considered invalid; if the difference is less than a certain threshold, the current filtering algorithm is considered effective. When there is a significant difference between the two calculation results, it is necessary to evaluate the current algorithm. Whether the current filtering algorithm is effective is evaluated and determined, and then corrections are made to it. During the iteration process, if the corrected result still does not meet the requirements, it is necessary to restart the optimization of the filter. The observed values are normalized after each iteration. In the normalization process, it is necessary to compare the current filter estimation result with the true value. When significant differences are found between the two through comparison, it indicates that the current filtering estimation algorithm is ineffective [16]. In the process of error analysis, the least squares method is used to perform error analysis on the positioning results. When it is found that there is a certain gap between the positioning results and the actual values through comparing the positioning results and error analysis results, the data needs to be reprocessed.

In specific environments such as urban canyons and indoors, multipath effects, occlusions, and reflections can significantly affect the positioning accuracy of GNSS signals, resulting in increased positioning errors or signal loss. To enhance the generalization of the algorithm, in urban canyons, multipath signals and occlusions caused by dense high-rise buildings may lead to instability in positioning results. In such cases, signal filtering and multi-sensor fusion methods can be used to improve stability. In indoor environments, signal reflections and occlusions also seriously affect positioning accuracy. Inertial navigation compensation can effectively alleviate such problems. In areas with complex occlusions such as mountains or forests, the positioning instability caused by irregular reflections can be improved by dynamically adjusting the filtering parameters. Analysis of different environmental factors will provide a reliable basis for algorithm optimization, enabling it to demonstrate greater stability and accuracy in a variety of scenarios.

5. Experimental results

The purpose of this experimental design is to evaluate and compare the performance of traditional positioning methods and multi-frequency and multi-system GNSS positioning data fusion algorithms based on Kalman filtering in terms of positioning accuracy, stability, and anti-interference ability. The experiment first collects positioning data and applies traditional positioning methods and Kalman filtering algorithm for analysis. In terms of positioning accuracy, the highest, lowest, and average positioning accuracy of the two methods are recorded and compared, as shown in **Figure 4**.

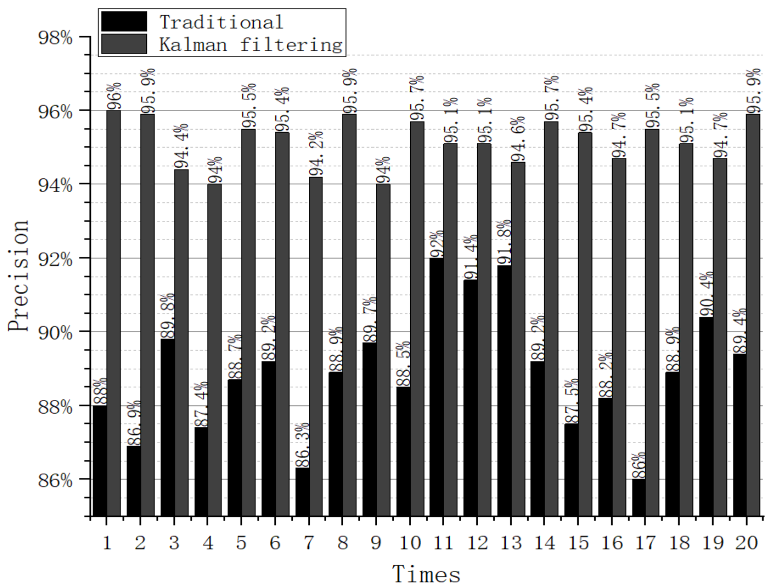

Figure 4. Positioning accuracy.

In **Figure 4**, the traditional positioning method has a highest positioning accuracy of 92% and a lowest accuracy of 86%, with an average calculated accuracy of 88.91%; the positioning accuracy of the multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filtering is as high as 96%, as low as 94%, and the calculated average accuracy is 95.14%. The multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filtering has higher positioning accuracy. This article conducts research and analysis on the adaptability of various frequency bands, as shown in **Table 1**.

Table 1. Adaptability.

System type	Frequency bands	Compatibility	Application scenarios
GNSS L1	1.575 GHz	High	Civilian applications
GNSS L2	1.227 GHz	Medium	Military applications
GNSS L5	1.176 GHz	High	Aviation and critical applications
BeiDou	B1, B2	High	Asian regional applications
Galileo	E1, E5	Medium	High-precision navigation

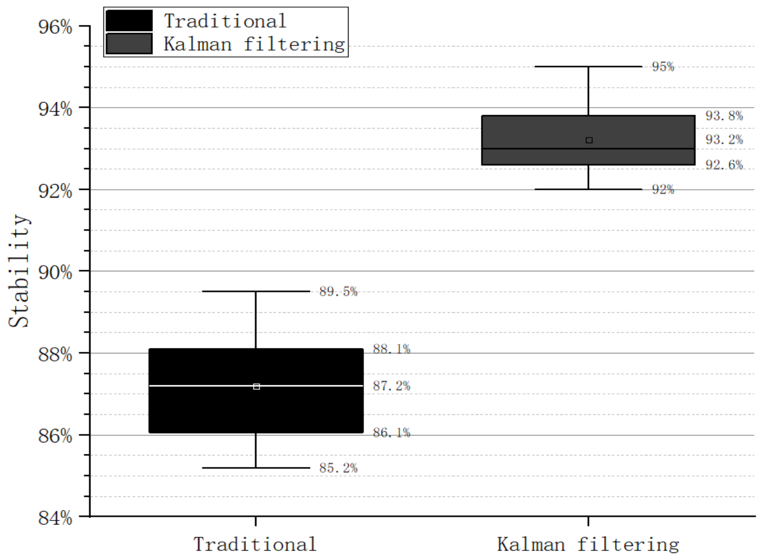

Figure 5. Stability.

In **Table 1**, the GNSS L1 frequency is 1.575 GHz, which has high compatibility and is mainly used for civilian applications such as car navigation and mobile positioning; the GNSS L2 frequency is 1.227 GHz, with moderate compatibility, mainly used for military applications, providing certain encryption and anti-interference capabilities; the GNSS L5 frequency is 1.176 GHz, with high compatibility, specifically designed for aviation and critical applications, suitable for high safety requirements. The BeiDou system uses the B1 and B2 frequency bands with high compatibility, mainly serving the Asian region and widely used in fields such as transportation, communication, and public safety; the Galileo system, on the other hand, uses the E1 and E5 frequency bands, with medium to high compatibility and a focus on high-precision navigation. It is suitable for applications that require high reliability, such as autonomous driving and precision agriculture. Through these frequency bands, GNSS systems provide flexible positioning services for various needs, covering a wide range of applications from civilian to military, from daily navigation to aviation safety. The stability test calculates the stability indicators of two methods under different environmental conditions, as shown in **Figure 5**.

In **Figure 5**, the stability of the traditional positioning method is highest at 89.5% and lowest at 85.2%, and the calculated average accuracy is 87.2%; the stability of the multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filtering is highest at 95% and lowest at 92%, and the calculated average accuracy is 93.2%. The multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filtering has higher stability. This article explores the computational complexity of each algorithm step to evaluate its feasibility in practical applications, as shown in **Table 2**.

Table 2. Calculation complexity.

Algorithm step	**Time complexity**	**Space complexity**	**Comments**
State prediction	O(n)	O(n)	Linear with state dimension
Measurement update	O(n^2)	O(n)	Depends on the number of measurements
Error covariance update	O(n^3)	O(n^2)	Computationally intensive
Data fusion	O(m)	O(m)	M: Number of data sources
Process noise estimation	O(n)	O(1)	Negligible for large n

In **Table 2**, the time and space complexity of state prediction are both O(n), linearly related to the state dimension, indicating that the required time and space are proportional to the estimated state size. Secondly, the time complexity of the measurement update is $O(n^2)$, and the space complexity is O(n), which increases squared and depends on the number of measurements. As the number of measurements increases, the processing time may significantly increase. Error covariance update is a computationally intensive step with a time complexity of $O(n^3)$ and a space complexity of $O(n^2)$, which may become a bottleneck in larger state dimensions. The time and space complexity of data fusion are both O(m), linearly related to the number of data sources (M), and can efficiently integrate information from multiple sources. Finally, the time complexity of process noise estimation is O(n), and the space complexity is O(1). For large-scale states, their space requirements can be ignored, indicating that this step is efficient in terms of memory usage. Overall, the algorithm demonstrates various complexities in different steps, with high efficiency in state prediction and process noise estimation, while measurement updates and error covariance updates face greater computational challenges when dealing with larger states or measurements. The experiment also evaluates the anti-interference ability of the system by analyzing the effectiveness of different types of interference and their corresponding anti-interference technologies to understand the performance of each technology in practical applications, as shown in **Table 3**.

Table 3. Anti-interference capability.

Jamming type	Anti-jamming technique	Effectiveness	Mitigation strategy
Narrowband jamming	Frequency hopping	69%	Rapid frequency switching
Wideband jamming	Adaptive filtering	85%	Signal processing techniques
Spoofing	Signal authentication	87%	Cryptographic checks
Thermal noise	Signal averaging	73%	Longer observation intervals
Multi-path interference	Spatial filtering	84%	Antenna design improvements

In **Table 3**, narrowband interference can be resisted through frequency hopping techniques, with an effectiveness of 69%, and fast response to interference can be achieved by quickly switching frequencies. For broadband interference, the effect of adaptive filtering technology is more significant, reaching 85%, and its mitigation strategy relies on signal processing technology to improve reception quality. The effectiveness of implementing signal authentication technology for deception attacks is 87%, ensuring the authenticity of signals through encryption checks. In the face of thermal noise issues, the effectiveness of signal averaging technology is 73%, and it is recommended to use longer observation intervals to reduce the impact of noise. These technologies and strategies together constitute effective means of resisting various interferences, enhancing the system's anti-interference ability. This article provides empirical evidence for the future development of GNSS positioning technology by comprehensively comparing various reliability indicators, including availability, integrity, accuracy, robustness, and redundancy, as shown in **Table 4**.

Table 4. Reliability.

Reliability Metric	Value	Description	Importance in GNSS
Availability	> 99%	Probability of system being operational	Critical for continuous positioning
Integrity	99.90%	Confidence that output is trustworthy	Essential for safety-critical applications
Accuracy	< 5 m	95% of positioning error	Direct impact on navigation quality
Robustness	Resilient to environmental changes	System's ability to maintain performance	Vital for dynamic conditions
Redundancy	Multiple frequency systems	Backup systems available	Improves system reliability

In **Table 4**, an availability exceeding 99% indicates a probability that the system is in an operational state, which is crucial for continuous positioning. Secondly, the integrity is 99.90%, reflecting the credibility of the output results, which is particularly important in safety critical applications to ensure that users can trust the information provided by the system. Regarding accuracy, 95% of positioning errors are within 5 meters, which directly affects navigation quality. Accurate positioning is the foundation of user safety and efficiency. Robustness refers to the resilience of a system under environmental changes, emphasizing its ability to maintain performance, which is crucial under dynamic conditions to ensure reliable operation in various environments. Finally, redundancy provides backup through a multi-frequency system, further improving the reliability of the system. In GNSS, these indicators work together to ensure high performance and reliability of the system, providing users with stable and safe navigation services.

This paper compares the traditional method and the multi-frequency multi-system GNSS positioning data fusion algorithm based on Kalman filtering in terms of positioning accuracy, stability, anti-interference ability, etc. Through the analysis of experimental data and performance indicators, the adaptability and reliability of the two methods in different environments are demonstrated. **Table 5** lists the specific data to help you deeply understand the advantages and differences of the two algorithms.

Table 5. Performance comparison of different positioning algorithms.

Performance Metric	Traditional Method	Kalman Filter Algorithm
Position Accuracy (%)	86–92	94–96
Average Position Accuracy (%)	88.91	95.14
Stability (%)	85.2–89.5	92–95
Average Stability (%)	87.2	93.2
Computational Complexity	O(n)	O(n)–O(n^3)
Anti-interference Ability	Low	High
Adaptability (Frequency Bands)	L1	L1, L2, L5, B1, B2, E1, E5
Environmental Adaptability	Moderate (large interference)	Strong (adjustable filtering parameters for dynamic environments)

According to the data in **Table 5**, the Kalman filter algorithm performs significantly better than the traditional method in terms of positioning accuracy and stability. The positioning accuracy of the traditional method fluctuates between 86% and 92%, while the positioning accuracy of the Kalman filter algorithm is between 94% and 96%, and the average accuracy is improved by about 6.23%. In terms of stability, the stability of the traditional method is between 85.2% and 89.5%, while the stability of the Kalman filter algorithm is maintained between 92% and 95%, and the average stability is improved by about 6%. In terms of computational complexity, the traditional method is relatively simple, mainly O(n), while the complexity of the Kalman filter algorithm at different stages is more diverse, reaching O(n^3). In terms of anti-interference ability, the Kalman filter algorithm shows stronger anti-interference characteristics and can better cope with signal interference and noise in dynamic environments. The Kalman filter algorithm has significant advantages in accuracy, stability and anti-interference ability.

6. Conclusions

This article explored in depth the advantages of the multi-frequency and multi-system GNSS positioning data fusion algorithm based on Kalman filtering in terms of positioning accuracy, stability, and anti-interference ability. The experimental results showed that the positioning accuracy and stability using this algorithm were significantly better than traditional positioning methods, reaching 95.14% and 93.2%, respectively. In addition, by analyzing the adaptability of different frequency bands and the reliability indicators of the system, the efficiency and reliability of multi-frequency and multi-system in dynamic environments were confirmed. Especially in terms of anti-interference ability, adopting appropriate technologies and strategies can effectively improve the stability and anti-interference ability of the system, providing a solid foundation for high-precision positioning. Meanwhile, the evaluation of computational complexity in the experiment also provides a reference for the practical application of optimization algorithms. Future research can continue to focus on further improving the accuracy and reliability of GNSS systems to cope with constantly changing environments and application requirements, thereby promoting the progress and development of navigation technology.

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