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Article

Research on High-precision Navigation Data Processing Under Communication Channel Optimization

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Abstract: High-precision navigation data are exceptionally vulnerable to channel fading, background noise, multipath interference, link delay, and packet loss within complex wireless communication applications. To address these critical challenges, the intricate coupling between communication channel optimization and robust navigation data processing is comprehensively considered in this study. Based on the fundamental principles of navigation data transmission and the mechanisms of channel degradation, a novel channel state awareness and data fusion processing framework tailored for high-precision navigation applications is systematically developed. Within this proposed framework, key performance indicators, including the signal-to-noise ratio (SNR), bit error rate (BER), packet loss rate (PLR), and transmission delay, are considered as primary observations to fully evaluate the reliability of the communication link. Subsequently, the channel quality evaluation results are seamlessly integrated into navigation data preprocessing, anomaly detection, dynamic weight allocation, and error feedback correction mechanisms. To validate the proposed methodology, five distinct simulation scenarios—encompassing normal channel conditions, low SNR, multipath effects, high packet loss, and dynamic occlusion—are rigorously tested. These simulation scenarios are quantitatively compared with traditional Kalman filtering, weighted least squares, and ordinary multi-source fusion techniques. The results demonstrate that the navigation data processor, when constrained by channel optimization limits, can significantly decrease the mean positioning error in a complex environment. Furthermore, it substantially improves overall data accuracy and trajectory continuity. Ultimately, this research provides substantial engineering reference value for civil aviation navigation data links, airport surface movement guidance, airborne GNSS/INS integrated navigation, and BeiDou/GNSS-based high-precision aviation terminals.

Keywords: channel optimization; civil aviation; data fusion; integrated navigation; state awareness

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1. Introduction

High-precision navigation data processing supports civil aviation navigation, aircraft approach and landing guidance, airport surface movement control, airborne GNSS/INS integrated navigation, and precision mapping. With the design of multi-source sensing devices, such as BeiDou Navigation Satellite System, Global Navigation Satellite System (GNSS), Inertial Measurement Unit (IMU), ultra-wideband positioning, and visual sensors, navigation has evolved from single positioning to multi-source fusion, continuous estimation, and real-time decision making. Navigation data must be accurately collected, transmitted, exchanged, and fed back via wireless links. The quality of communication channels is a critical factor influencing navigation data processing. Research indicates that GNSS observations during airport surface taxiing, terminal-area flight, low-altitude approach, and operations near hangars or complex airport buildings are susceptible to obstructions, multipath effects, and signal attenuation. While multi-scale fusion can enhance the accuracy of single sensors, it is hindered by link delay, packet loss, and channel noise.

There is significant potential in relatively mature error modeling and filtering methods for high-precision navigation. Techniques such as Kalman filtering, extended Kalman filtering, factor graph optimization, PPP-RTK, GNSS/INS tight combination, and visual/LiDAR-assisted positioning methods are widely used for navigation state estimation. These methods primarily model observation noise, sensor drift, and state estimation uncertainty but often fail to explicitly account for reliability changes caused by channel degradation. In civil aviation scenarios, including ADS-B-based surveillance, GBAS/SBAS correction transmission, airborne-ground data links, and airport surface cooperative positioning, navigation-related information must be transmitted via reliable communication links. The stability of these links directly impacts the availability of navigation data [1, 2]. Using fixed observation noise or fixed weights for processing can lead to system drift, land jump, or filter divergence under degraded channel conditions.

Optimizing communication channels involves not only improving data transmission performance but also enhancing the accuracy of navigation data processing. The channel state reflects the reliability of current data transmission, enabling navigation data models to adjust the weighting of observation data based on channel quality. When channel quality is high, the weight of current observation data in state updates may be increased; conversely, when channel quality deteriorates, abnormal observations can be minimized, and historical state predictions, related sensor data, and error feedback can be utilized to maintain consistent navigation results. Consequently, mapping the communication channel state into navigation data processing is essential [2].

This paper introduces a robust navigation data processing technique tailored for complex communications [3]. Unlike general intelligent transportation navigation, this study emphasizes channel-degraded navigation data processing in civil aviation scenarios, including airborne navigation data transmission, airport surface positioning, and approach-related correction information. The primary contributions are as follows: signal-to-noise ratio, bit error rate, packet loss rate, and transmission delay are used as channel quality criteria; channel quality is incorporated into navigation data anomaly identification and dynamic weight fusion; and positioning error, data integrity, and trajectory stability of different algorithms under complex channel conditions are compared through simulation experiments, providing a practical technical reference for engineering applications.

2. The Impact Mechanism of Communication Channels on Navigation Data Processing

High-precision navigation data exhibits continuity, temporal order, real-time characteristics, and multi-source integration. In a typical navigation system, data sources include satellite pseudo range, carrier phase, Doppler, inertial measurements, airborne inertial measurements, barometric altitude data, airport surface positioning observations, visual/laser-assisted sensing information, and differential correction messages from ground reference stations. These sources vary in sampling frequencies, accuracies, errors, and transmission methods, necessitating data fusion through time reference and spatial coordinate alignment. Under normal conditions, navigation data arrives at specified frequencies, enabling regular filter updates. However, if communication channel quality declines, the temporal structure of the data may be affected, potentially impacting state estimation results.

A reduction in signal-to-noise ratio can degrade communication channel performance, where weak signal energy or high background noise generates random fluctuations in navigation observations, leading to local jitter and error variance in measurements. Even short-term observation variations can influence long-term vehicle trajectories [4, 5]. Multipath signals reflected by buildings, ground surfaces, or metallic facilities may introduce systematic observation offsets. These errors are often scene-dependent and may not conform to Gaussian distributions. Multipath errors exhibit scene correlation and non-Gaussian behavior, which traditional filtering methods cannot fully suppress. Figure 1 illustrates the influence mechanism of communication channel conditions on high-precision navigation data processing.

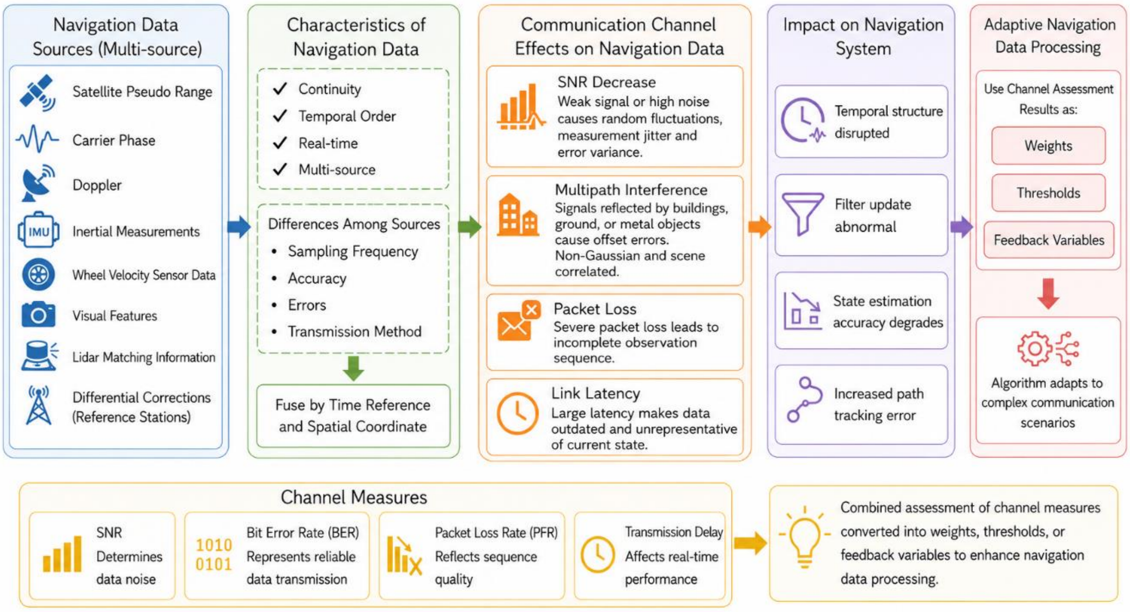

Figure 1. Influence Mechanism of Communication Channel Conditions on High-Precision Navigation Data Processing

Packet loss and link latency directly impact the continuity and real-time availability of navigation data. In airport surface movement guidance and airborne-ground cooperative navigation, aircraft, ground stations, and airport surveillance facilities frequently exchange positioning status and correction information. Severe packet loss prevents the system from obtaining a complete observation sequence, while significant latency renders received data unrepresentative of the current motion state. For aircraft taxiing, approach guidance, and low-altitude flight, outdated navigation or correction data can increase track deviation and reduce the reliability of guidance information. Navigation data processing algorithms must account for both packet loss and latency [3].

The influence of communication channels on navigation data processing often involves multiple factors rather than a single measure. Signal-to-noise ratio determines data noise levels, bit error rates reflect transmission reliability, packet loss affects sequence quality, and latency impacts real-time performance [6]. By assessing these measures and converting evaluation results into weights, thresholds, or feedback variables, navigation data processing algorithms can adapt to complex communication scenarios.

3. Navigation Data Processing Methods under Channel Optimization

This study mainly discussed five different processing processes: channel state awareness, navigation data preprocessing, anomaly observation recognition, dynamic weight fusion, and error feedback correction. The system first collects navigation observation data and communication link state parameters and synchronizes the time and coordinates of different data sources. Subsequently, it assesses data reliability and anomaly observation [4]. The preprocessed data enter the fusion module, in which a dynamic weighting function calculates the contribution of different sources to state estimation and a feedback correction based on historical trajectories and current residuals. The overall algorithm consists of five modules: channel state acquisition, data preprocessing, anomaly detection, dynamic weight fusion, and feedback correction. At each epoch, the system first receives navigation observations and channel indicators, then normalizes the channel indicators, evaluates channel quality, identifies abnormal observations, updates fusion weights, and finally outputs the corrected navigation state.

The channel state awareness module is the foundation of our method [7, 8]. This module does not directly modify the navigation data itself, but rather provides a basis for quality evaluation in subsequent processing. The study selected the signal-to-noise ratio (SNR), bit error rate (BER), packet loss rate (PLR), and transmission delay as the main channel indicators. To ensure that all channel indicators are mapped into the same range, SNR, BER, PLR, and delay are normalized to. The normalized SNR is calculated by min-max mapping, where a larger value indicates better channel quality. BER, PLR, and delay are also normalized by min-max mapping, but they are introduced into the quality function in a complementary form because smaller values indicate better transmission reliability. To eliminate the differences in the dimensions of different indicators, the study first normalized the SNR, BER, PLR, and transmission delay at time k, defining the comprehensive channel quality index as follows:

$$Q_k = \alpha_1\widehat{SNR}_k + \alpha_2\left(1-\widehat{BER}_k\right) + \alpha_3\left(1-\widehat{PLR}_k\right) + \alpha_4\left(1-\widehat{D}_k\right), \quad \sum_{i=1}^{4}\alpha_i = 1 \quad (1)$$

In the formula, Q_k represents the comprehensive channel quality index at time k; $\widehat{SNR}_k, \widehat{BER}_k, \widehat{PLR}_k$, and $\widehat{D}_k$ represent the normalized signal-to-noise ratio, bit error rate, packet loss rate, and transmission delay, respectively; α_i is the weighting coefficient of each channel index. The engineering empirical coefficients are set as α_1 =0.4, α_2 =0.2, α_3 =0.2, and α_4 =0.2. A larger weight is assigned to SNR because signal strength has a direct influence on observation stability in civil aviation navigation links. The remaining three indicators are given equal weights to reflect transmission reliability, sequence completeness, and real-time performance. Since a higher signal-to-noise ratio is more advantageous, while a lower bit error rate, packet loss rate, and transmission delay are more advantageous, the latter three indices are incorporated into the evaluation function in a complementary manner [2].

The navigation data preprocessing module mainly handles data cleaning, time alignment, and gross error removal. Because the multi-source navigation data have different sampling times, direct fusion may cause a time mismatch. In this paper, the study utilizes the same time window to set the data, mapping GNSS, INS, and other sensor information within the same window to the same processing time. For missing or formatted data, the study marks it first, instead of deleting it directly, because short-term data loss may occur if communication channels degrade; simply deleting data would cause long state sequences.

The anomaly detection module considers both navigation residuals and channel quality [9, 10]. Let the observation value of the i-th sensor at time k be $z_{i,k}$, and the model predict the observation value as $h_i\left(\hat{x}_{k|k-1}\right)$. Then the normalized residual can be expressed as:

$$r_{i,k} = \frac{\left\|z_{i,k} - h_i\left(\hat{x}_{k|k-1}\right)\right\|}{\sigma_{i,k}+\varepsilon} \quad (2)$$

In the formula, $r_{i,k}$ represents the normalized observation residual; $\hat{x}_{k|k-1}$ represents the navigation state predicted from the previous time step; $h_i(\cdot)$ represents the i-th type of observation equation; $\sigma_{i,k}$ represents the standard deviation of the observation noise; and ε is a minimal constant to prevent the denominator from being zero. When $r_{i,k}$ is large and Q_k is low, the system reduces the fusion weight of the observation source, rather than simply removing it completely. The anomaly decision rule is defined as follows. If $Q_k < Q_{th}$ and $\gamma r_{i,k} > r_{th}$, the observation is marked as unreliable and its fusion weight is reduced. In the simulation, Q_{th} is set to 0.6 and rth is set to 3.0. This rule avoids directly deleting observations and is more suitable for short-term channel degradation.

Dynamic weight fusion is the core of our proposed method [11]. Traditional multi-source fusion methods typically assign fixed weights to different data sources, such as increasing the weight of GNSS observations or inertial measurement data. However, in complex communication environments, fixed weights are insufficient to reflect real-time data quality. In this study, we adjusted the data weights based on channel quality, observation stability, and historical error performance. The dynamic weight of the i-th data source at time k is defined as follows:

$$w_{i,k} = \frac{\exp(\beta Q_{i,k} - \gamma r_{i,k} - \eta e_{i,k-1})}{\sum_{j=1}^{N} \exp(\beta Q_{j,k} - \gamma r_{j,k} - \eta e_{j,k-1})} \quad (3)$$

In the formula, $w_{i,k}$ is the dynamic fusion weight of the i-th type of data source; $Q_{i,k}$ represents the channel quality of the corresponding data source; $r_{i,k}$ represents the current observation residual; $e_{i,k-1}$ represents the historical error of the data source at the previous time step; N represents the number of data sources; γ and η control the influence of channel quality, observation residual, and historical error on weight allocation, respectively. The parameters are set as $\beta = 1.0$, $\gamma = 0.8$, and $\eta = 0.5$ based on engineering experience in civil aviation channel-degraded scenarios. This setting gives priority to channel quality, while residual deviation and historical error are used as auxiliary factors.

After weight allocation, the multi-source navigation state fusion result can be expressed as

$$\hat{x}_k = \sum_{i=1}^{N} w_{i,k}\, \hat{x}_{i,k}, \quad 0 \le w_{i,k} \le 1, \quad \sum_{i=1}^{N} w_{i,k} = 1 \quad (4)$$

In the formula, $\hat{x}_k$ represents the fused navigation state estimate; $\hat{x}_{i,k}$ represents the state estimate obtained independently from the i-th type of data source. This expression ensures that all weights are within the effective range while maintaining the physical interpretability of the fused result.

An error feedback correction module is used to improve trajectory continuity. Short-term errors are unavoidable during continuous operation of the navigation system, but if these errors are not corrected in time, they will gradually accumulate and cause trajectory deviation. This study uses historical state estimation results and the current fused residuals to form a feedback correction amount to smooth local trajectories [12]. The corrected navigation output is as follows:

$$\tilde{x}_k = \hat{x}_k + \lambda(\hat{x}_k - \hat{x}_{k-1}) + (1-\lambda)K_k\big(z_k - h(\hat{x}_k)\big) \quad (5)$$

In the formula, $\tilde{x}_k$ represents the navigation state after feedback correction; λ is the trajectory continuity adjustment coefficient; K_k is the feedback gain matrix; and $z_k - h(\hat{x}_k)$ represents the current observation residual term. The feedback coefficient is set as $\lambda = 0.3$. This value provides moderate trajectory smoothing without changing the original motion trend of the aircraft or ground vehicle. This module does not aim to change the carrier's motion trend, but rather to suppress local jumps caused by channel fluctuations, making the navigation output more stable.

4. Simulation Experiment Design

To validate the proposed method, a two-dimensional civil aviation navigation simulation was conducted, encompassing airport surface taxiing and terminal-area movement under degraded communication channels. The simulation trajectory included straight taxiing, turning, short-term acceleration, and speed stabilization, aligning with typical airport surface and terminal-area movement patterns. A realistic trajectory was generated at a fixed frequency, with navigation observation noise, communication channel noise, multipath error, and random packet loss superimposed on this trajectory. The simulation experiment aimed to compare the adaptability of various data processing methods to channel degradation under controlled conditions, rather than serving as a substitute for real-world testing [13].

The study established four comparison methods: 1) Kalman filtering, which utilized fixed observation noise settings and estimated state as input; 2) weighted least squares, which applied weight adjustments to the underlying observations; 3) ordinary multi-source fusion, incorporating GNSS, INS, and additional sensors without accounting for communication channel states; and 4) the method proposed in this study, which integrated channel state awareness, abnormal observation identification, and error feedback correction.

The scenarios included normal channel conditions, low signal-to-noise ratio, multipath interference, high packet loss rate, and dynamic occlusion [14]. The normal channel scenario tested the algorithm's baseline performance; the low signal-to-noise ratio scenario simulated long-distance communication, weak signals, or strong background noise; the multipath interference scenario represented environments such as airport aprons, terminal buildings, hangars, and runway-side reflective areas; the high packet loss rate scenario addressed link instability or congestion; and the dynamic occlusion scenario modeled aircraft taxiing near terminal buildings, ground service vehicles around aprons, and temporary signal blockages in terminal-area environments.

The evaluation metrics included measurable positioning error, root mean square error (RMSE), data integrity rate, mean transmission delay, and trajectory stability. Mean positioning error quantified the overall deviation between the positioning result and the true trajectory; RMSE provided sensitivity to larger errors and robustness in complex scenarios; data integrity rate measured the percentage of valid navigation data processed; mean transmission delay assessed the impact of link performance on real-time operations; and trajectory stability evaluated the extent of continuous shifts in positioning points.

5. Experimental Results and Analysis

The performance of all methods under five-channel conditions is summarized in Table 1. Under normal channel conditions, all methods maintain acceptable positioning performance, while the proposed method achieves the lowest average positioning error. This demonstrates that dynamic weight fusion and feedback correction remain effective even when the channel is relatively stable. Traditional multi-source fusion methods may increase errors due to redundancy; however, as they lack channel state evaluation, they exhibit significant fluctuations under high packet loss rates and dynamic conditions.

Table 1. Comparison of Positioning Errors of Different Methods under Complex Channels

method	Normal channel /m	Low signal-to-noise ratio/m	Multipath /m	High packet loss/m	Dynamic occlusion /m
Traditional Kalman Filter	0.42	0.86	1.12	1.35	1.48
Weighted Least Squares	0.46	0.91	1.25	1.42	1.56
Ordinary multi-source fusion	0.35	0.72	0.94	1.08	1.21
This article's method	0.28	0.51	0.63	0.74	0.82

Our method demonstrates relative stability under poor channel quality, as the system can automatically adjust weights based on the channel type. When the communication quality of a data source decreases, the method reduces its contribution and increases reliance on stable sources and state prediction. Consequently, abnormal observations are not directly amplified in the fusion result, ensuring trajectory continuity [15]. In dynamic occlusions, the trajectory changes produced by the method are smoother, avoiding sudden deviations.

The data integrity rate results are presented in Table 2. Under normal channel conditions, the differences in data integrity rates between the methods are minimal. However, under high packet loss conditions, the data integrity of traditional methods declines rapidly. The proposed method maintains effective data integrity by marking and compensating for short-term missing data. Instead of filling all missing data, the method determines the reliability range of the compensated data based on channel conditions and historical trajectories [16]. If the packet loss duration exceeds a fixed window, the confidence in the prediction results is reduced to prevent over-reliance on speculative compensation data.

Table 2. Ablation Experiment Results

Model settings	Average error /m	Root mean square error / m	Data completeness rate / %
Remove channel quality assessment	0.71	0.88	92.4
Remove anomaly observation identification	0.79	0.96	93.2
Remove error feedback correction	0.68	0.84	94.1
Complete model	0.49	0.63	96.2

As shown in Figure 2, the conventional Kalman filtering method exhibits continuous small-amplitude jitter in low signal-to-noise ratio stages and local offsets in multipath stages. The weighted least squares method is highly sensitive to single-point noise and sudden jumps. The standard multi-source fusion method maintains trajectory continuity but accumulates errors in blocked regions [4, 6]. In contrast, the proposed method effectively suppresses local anomalies through anomaly observation and error feedback correction. Its channel quality assessment enhances data fusion accuracy, improving the engineering applicability of civil aviation navigation trajectories, particularly for airport surface movement, airborne-ground correction transmission, and terminal-area navigation continuity.

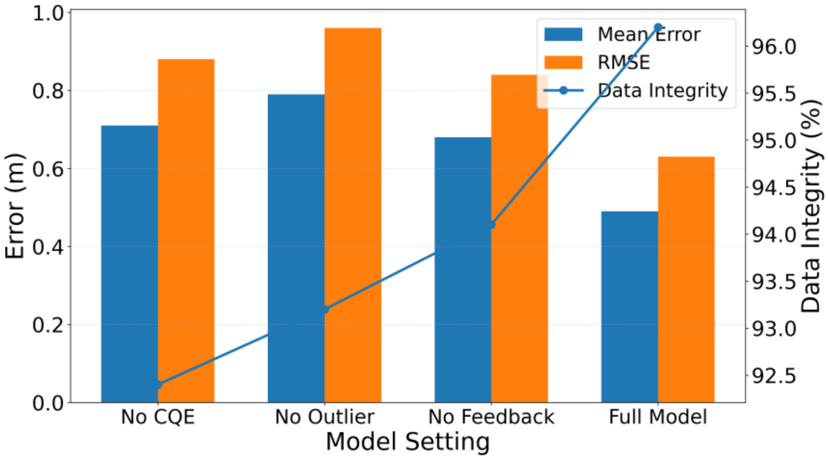

Figure 2. Ablation Results of Different Model Settings

6. Conclusion

This study investigated high-precision navigation data processing with communication channel optimization. Specifically, a data processing method integrating channel state awareness, anomaly detection, dynamic weight fusion, and error feedback correction was proposed. First, the effects of signal-to-noise ratio (SNR), bit error rate (BER), packet loss rate (PLR), and transmission delay on navigation data integrity, real-time performance, and positioning accuracy were analyzed. Subsequently, a channel quality-driven navigation data processing framework was established. Simulation results showed that, compared with traditional Kalman filtering, weighted least squares, and conventional multi-source fusion methods, the proposed approach achieved lower positioning errors and higher data integrity under normal channels, low SNR, multipath interference, high packet loss rates, and dynamic occlusion. The results indicate that communication channel optimization should be addressed not only at the data transmission level but also within the navigation data processing framework. By mapping channel states to fusion weights, anomaly criteria, and feedback correction parameters, the proposed method enhances the stability and reliability of high-precision navigation in degraded channel environments. The method is particularly applicable to civil aviation scenarios, including airborne GNSS/INS integrated navigation, ADS-B and ground-air data-link-assisted positioning, GBAS/SBAS correction transmission, airport surface movement guidance, and BeiDou/GNSS high-precision aviation terminals.

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