Dynamic multidimensional sensor data acquisition with adaptive Kalman filtering

Bing Yu[1]

[1]School of Geomatics and Urban Spatial Information, Beijing University of Civil Engineering and Architecture, Beijing 102616,China- 2108570023119@stu.bucea.edu.cn

Keywords: Adaptive Kalman Filter, Multidimensional Sensor Data, Gait Awareness, Real-Time Data Acquisition.

Abstract

Traditional mobile sensing systems often experience a decline in data acquisition accuracy in dynamic environments due to the use of fixed-parameter Kalman filters, which lack adaptability to changes in motion states and sensor noise. To address this limitation, this paper proposes a gait-aware adaptive Kalman filtering method that dynamically adjusts filter parameters based on real-time gait frequency analysis. This method enables autonomous real-time data collection of multi-dimensional data from multiple sensors embedded in smartphones. By employing adaptive covariance optimization, the method enhances the system's ability to handle different motion patterns, ensuring the accuracy and robustness of data collection. Experimental results demonstrate that this method improves data quality in diverse motion scenarios, providing a reliable foundation for multi-modal sensing and intelligent mobile sensing applications.

1. Introduction

With the rapid development of mobile computing technology, smartphones have evolved beyond mere communication tools to become multifunctional intelligent platforms integrating location tracking, sensing, and interaction capabilities. One of the key drivers behind this transformation is the continuous maturation of built-in sensor technology and enhanced integration capabilities. Currently, mainstream smart devices are generally equipped with various types of sensors, including inertial sensors (such as accelerometers, gyroscopes, and magnetometers), location sensors (such as GPS), and environmental sensing sensors (such as thermometers, light sensors, and barometric pressure sensors)(Zheng et al., 2020). These sensors can collect real-time data on user movements and environmental conditions, providing devices with precise contextual awareness capabilities.

Sensor data is widely used in functions such as automatic screen rotation, gesture recognition, and motion state detection, significantly enhancing the naturalness and convenience of human-computer interaction. It also provides a solid data foundation for fields such as pedestrian navigation, motion analysis, and behavior recognition. However, due to the physical limitations of sensors, their accuracy and response capabilities are often affected by the stability of the external environment and the complexity of motion patterns. When users are in situations with significant changes in gait or dynamic interference, traditional sensor data collection mechanisms often experience issues such as reduced accuracy or response delays, which in turn affect the stability and robustness of upper-layer application systems.

Among various sensor application scenarios, indoor positioning has emerged as a research hotspot due to the high-precision location sensing requirements in complex dynamic environments. Unlike outdoor environments, which can rely on GNSS systems to provide stable positioning information, indoor environments are characterized by significant signal obstruction, reflection, and multipath effects, leading to a significant decline in the effectiveness of traditional positioning methods(Zhao et al., 2019). To overcome this bottleneck, researchers have gradually turned to relying on time-series data collected by multi-source sensors in mobile devices to characterize user behavior patterns and environmental states, thereby achieving indirect modeling of location and trajectory. Against this backdrop, in recent years, a large number of studies have introduced deep learning methods, leveraging their powerful feature extraction and spatio-temporal modeling capabilities, and have been widely applied to tasks such as indoor behavior recognition, trajectory prediction, and auxiliary positioning, achieving significant results(Poulose and Han, 2021). However, the modeling capabilities of deep learning models are highly dependent on the quality and stability of the raw sensor data. If the collected data contains noise interference, sampling discontinuities, or missing errors, it will directly weaken the model's ability to capture temporal patterns, thereby affecting training efficiency and inference accuracy. Therefore, how to achieve high-quality, multi-dimensional, and dynamically robust data collection mechanisms on mobile devices has become a critical prerequisite for the effective performance of deep sensing systems.

Among the many algorithms used for preprocessing inertial sensor data, the Kalman filter is widely used in mobile sensing systems due to its efficient state estimation capabilities and good real-time performance. It is used to reduce noise interference, smooth time-series data, and improve the reliability of observations(Lee et al., 2021). By dynamically adjusting the differences between the system state and observations, it can effectively improve the accuracy and consistency of sensor data under ideal conditions. However, traditional Kalman filter methods typically rely on statically defined process noise and observation noise covariance matrices, making them ill-suited to handle the non-stationary characteristics resulting from frequent changes in user behavior patterns. This is particularly evident in dynamic scenarios such as fast walking, turning, or complex gait patterns, where the filter may exhibit issues such as drift, over-smoothing, or error accumulation.

Therefore, in data-driven indoor intelligent sensing systems, establishing a stable, robust, and adaptable multi-dimensional sensor data acquisition mechanism capable of handling dynamic scene changes is a critical prerequisite for the practical application of model performance. The step frequency-aware adaptive Kalman filter method proposed in this paper is specifically designed to address this issue. By introducing a real-time step frequency adjustment mechanism to dynamically adjust filter parameters, the system can autonomously optimize the modeling of observations from sensors such as accelerometers, gyroscopes, and magnetometers based on changes in user behavior states. This significantly enhances the continuity, consistency, and physical plausibility of signal sampling at the data level. This method can serve as a crucial data foundation for subsequent deep learning models in time series modeling, feature extraction, and representation learning for perception tasks. Based on this method, a dynamic multi-dimensional sensor data acquisition app for the Android platform has been developed, enabling stable multi-source perception data collection and providing a reliable foundation for data modeling and environmental perception in indoor location services.

The remainder of this paper is organized as follows. Section 2 introduces related work. Section 3 introduces the proposed algorithm, including its architecture, experiments, and explanations. Section 4 evaluates the proposed algorithm in actual collection processes to prove its performance. Section 5 summarizes this paper.

2. Related Work

2.1 Noise covariance dynamic adjustment method

An improved Kalman filter is employed in mobile GNSS/IMU systems to fuse IMU data with different sampling frequencies with GNSS observations, demonstrating that an improved covariance configuration can significantly enhance the navigation performance of low-cost terminals(Yan et al., 2020). Chen Yu et al. proposed an adaptive Kalman filter method based on the EM algorithm for smartphone pedestrian navigation systems, which improves positioning accuracy in complex environments(Yu et al., 2020). Wu et al. proposed an adaptive Kalman filter method based on residual analysis for heading estimation in pedestrian dead reckoning, enhancing system robustness in dynamic environments(Wu et al., 2018). Sun proposed an innovative adaptive Kalman filter (IAKF) that dynamically identifies abnormal observations and adjusts the measurement noise covariance matrix by performing chi-square tests on the filter innovation quantities, effectively improving the robustness and anti-interference capabilities of INS/GNSS systems in complex urban environments(Sun et al., 2022). However, this approach heavily relies on anomaly detection, requires manual setting of the chi-square threshold, and only adjusts the observation covariance matrix, failing to account for system dynamic changes caused by user state variations. Pandey addressed the IMU attitude estimation problem by introducing a recursive information expansion Kalman filter (RI-EKF) based on the expectation-maximization (EM) algorithm, which improves attitude estimation accuracy through iterative estimation processes and measurement noise covariance(Pandey et al., 2024). However, the EM algorithm is computationally intensive and unsuitable for real-time embedded environments; additionally, parameter convergence speed depends on initialization, making it difficult to quickly respond to dynamic changes in user behavior.

2.2 Deep learning and filter fusion methods

Ghanizadegan proposed the DeepUKF-VIN framework, which combines the Unscented Kalman Filter (UKF) with the Visual Inertial Neural Network (IMU-Vision-Net) to enable online estimation of the noise covariance matrix, thereby enhancing positioning performance in indoor environments with weak GNSS signals(Ghanizadegan and Hashim, 2025). This method requires training a deep neural network model, which relies on large-scale labeled datasets; and the computational cost is high, making it difficult to deploy on general-purpose mobile devices. Levy proposed the Adaptive Neural UKF, which uses a neural network to predict state noise covariance, achieving good results in autonomous underwater vehicle (AUV) systems(Levy and Klein, 2025). Although it is adaptive, the network model is large and unsuitable for resource-constrained mobile platforms, lacking lightweight deployment strategies. Adžemović et al. proposed a deep learning-based Bayesian filtering method to improve the performance of target tracking systems, particularly excelling in handling nonlinear motion patterns(Adžemović et al., 2024). While these methods enhance filtering performance to some extent, they generally suffer from high model complexity, significant computational resource requirements, or reliance on large training datasets, making direct deployment on lightweight mobile terminals challenging.

2.3 Multi-sensor fusion and environment-adaptive filtering methods

Xie's AKF-LIO framework combines LiDAR and IMU, dynamically adjusting the weights and covariances of the two sensor types through context-aware strategies to enhance robustness in complex scenarios(Xie et al., 2025). AKF-LIO relies on multiple heterogeneous sensors (LiDAR + IMU), has high hardware requirements, and is not suitable for single mobile terminal environments; additionally, the system design is complex, resulting in high deployment barriers. Pang applied adaptive UKF to an IMU+GPS system in high-dynamic forest environments, using acceleration changes to automatically adjust measurement noise, making it suitable for sharp turns or complex terrain navigation(Pang et al., 2024). Although it considers dynamic motion, it only uses acceleration as the basis for adjustment, making it insensitive to low-speed or vibration-related motion changes; additionally, the scheme does not consider deployment efficiency under resource-constrained conditions.

An analysis of the current state of research both domestically and internationally has identified the following two issues:
(1) Fixed filter parameters with poor adaptability: Commonly used Kalman filters typically employ fixed observation noise covariance (R) during deployment. While this may be effective in static or single-motion scenarios, it fails to adapt promptly to changes in motion states and sensor noise characteristics in real-world scenarios where user gait frequently changes, leading to a decline in data filtering accuracy.
(2) Lack of a general, real-time adaptive mechanism: While some adaptive filtering methods possess a certain degree of adjustment capability, they largely rely on prior models or historical data fitting, resulting in poor generalizability and low real-time performance. This makes them unsuitable for continuous high-frequency data collection tasks on resource-constrained mobile devices.

3. Method

In this paper, an adaptive Kalman filtering method based on step frequency sensing is proposed, aiming at realizing high-precision acquisition of multi-dimensional sensor data in dynamic scenes. The method mainly includes two parts of the core mechanism: the step frequency sensing module and the filter parameter adaptive adjustment module, and the overall flow is shown in Figure 1.

On the data acquisition side, the system is based on the built-in accelerometers, gyroscopes and magnetometers of smartphones to realize real-time sensing of the user's motion state and raw data acquisition. In order to obtain the user's current step frequency characteristics, the system uses the acceleration signal for periodic analysis, combined with the peak detection algorithm to calculate the current step frequency in real time.

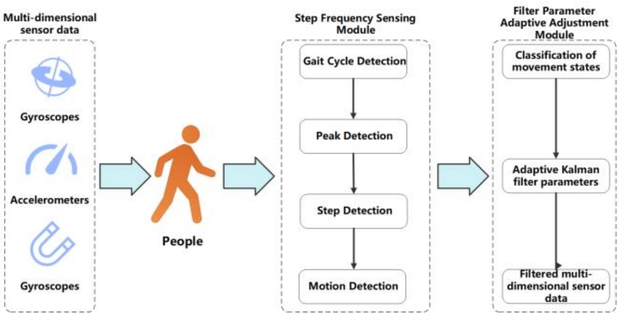

Figure 1. Technical flow of the method.

3.1 Kalman filtering method

The Kalman filter is a recursive filter used for state estimation in linear systems, suitable for dynamic systems under the assumption of Gaussian white noise. It uses the current system state prediction and measurement observations, combined with their respective uncertainties, to perform optimal estimation of the true state. Its system model consists of two parts: the state transition model and the observation model. State transition model:

$$x_k = Ax_{k-1} + Bu_k + w_k \tag{1}$$

x_k indicates the actual state of the system at time k ; A is the state transition matrix, which defines the evolution relationship between the state at the previous moment $k-1$ and the current moment k ; B is the control input matrix, and u_k is the current control input; w_k is process noise, which follows a Gaussian distribution $w_k \sim \mathcal{N}(0,Q)$.

The observation model is:

$$z_k = Hx_k + v_k \tag{2}$$

z_k represents the actual observation value of the system at time k ; H is the observation matrix, which maps the system state x_k to the measurement space; v_k is the measured noise, which follows a Gaussian distribution $w_k \sim \mathcal{N}(0,Q)$.

The entire Kalman filter process consists of two steps: prediction and update. It uses the system model to predict the state and covariance at the next moment:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \tag{3}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{4}$$

$\hat{x}_k^-$ is the current state prior estimate, and P_k^- is the prior error covariance. In the update phase, the current observation value is used to correct the prediction result and update the state estimate and covariance matrix:

$$K_k = P_k^- H^T (HP_k^- H^T + R_k)^{-1} \tag{5}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{6}$$

$$P_k = (I - K_k H)P_k^- \tag{7}$$

K is the Kalman gain matrix, which measures the weight of the observation value in the final estimate. If R_k is large, it indicates that the observation value noise is large, and the system will rely more on the predicted value; conversely, it will rely more on the current observation. In traditional implementations, Q and R are mostly preset constants, which are difficult to cope with the dynamic changes in the user's movement state in real scenarios, such as sudden starts, acceleration, sharp turns, and other behaviors.

3.2 Step frequency detection method

To achieve real-time sensing of the user's movement status, this study embedded a step frequency estimation module in the data collection process. This module mainly relies on the periodic fluctuations generated by the accelerometer sensor during human walking. Through time window sliding analysis and peak detection methods, it achieves real-time calculation of step frequency. The entire process includes four steps: cycle calculation, peak detection, and step frequency output. The original three-axis acceleration signal is converted into acceleration modulus to enhance the periodic expression capability of the signal:

$$a_{mag}(t) = \sqrt{a_x^2(t) + a_y^2(t) + a_z^2(t)} \tag{8}$$

During walking, the periodic fluctuations in the center of gravity of the human body cause the modulus signal to exhibit obvious periodic peaks. By setting a minimum time interval restriction condition, a set of local maximum time points $\{t_1, t_2, \cdots, t_n\}$ corresponding to the stride can be extracted from the modulus sequence. In this paper, the minimum time interval is 200ms. Calculate the current step frequency f_t based on the average interval between consecutive peaks:

$$f_t = \frac{n-1}{t_n - t_1} \tag{9}$$

This calculation is based on n peaks detected within the current time window, reflecting the user's walking rhythm per unit of time. Step frequency estimation uses a fixed time window for sliding updates. When new data arrives, the window content is updated, and peak extraction and frequency calculation are performed again to achieve dynamic tracking of step frequency.

In order to improve filter adaptability, this study proposes using the step frequency f_t as a dynamic feedback signal to adaptively adjust R_k in real time. The covariance adjustment formula is as follows:

$$R(f) = \begin{cases} R_{low}, & f \le f_{low} \\ R_{low} + k(f - f_{low}), & f_{low} < f < f_{high} \\ R_{high}, & f \ge f_{high} \end{cases} \tag{10}$$

where f = current detection step frequency
f_{low}, f_{high} = step frequency threshold boundary
R_{low}, R_{high} = corresponding R parameter value
$k = (R_{high} - R_{low}) / (f_{high} - f_{low})$

When users engage in more vigorous exercise, resulting in a higher step frequency, the uncertainty of observation noise increases. The filter should reduce its reliance on sensor observations and instead rely more on prediction terms. In a steady state, however, it should increase its reliance on observation terms. Without the need for predefined motion models or external calibration data, the system exhibits high adaptability and versatility, dynamically adjusting filtering strategies based on the user's natural behavior. By updating filter parameters in real time, it enhances the accuracy and robustness of multi-source data collection in actual dynamic environments.

4. Experimental evaluation

4.1 Experimental equipment and data acquisition

In this section, the feasibility and performance of the proposed adaptive Kalman filter method are validated through experiments. The Huawei Mate40 Pro smartphone was used as the test platform for method validation, with experimental hardware parameters as shown in Table 1. The corresponding algorithms were developed and software code implemented using Android Studio, with the sensor data acquisition frequency set to 50 Hz as mentioned in the paper.

Mobile phone model	Detailed parameters	
HUAWEI Mate 40 Pro	CPU model Memory apacity Operating system	Mali-G78 MP24 8GB RAM Harmony OS 2.0

Table 1. Detailed specifications of the mobile phone.

The experiments were conducted in an indoor corridor area of a building, with two gait modes set: normal walking and fast walking, to simulate real-world usage scenarios under different movement rhythms. During data collection, participants were required to naturally switch between the two gait modes, with a focus on covering the significant changes in step frequency. A total of approximately 80,000 frames of data were collected. Parameter settings in this paper $R_{low} = 0.01I, R_{high} = 0.005I$.

4.2 Experimental equipment and data acquisition

To evaluate the stability performance of the proposed step frequency sensing adaptive Kalman filter method in the process of multi-dimensional sensor data acquisition, this paper introduces the axis error distribution (AED) as the core evaluation metric. This metric analyzes the amplitude and deviation of fluctuations in three-axis sensor signals after filtering to reveal the differences in how various methods smooth the original sensor signals. Compared to using statistical measures such as the mean or standard deviation, the AED provides a more granular probabilistic statistical perspective, enabling the description of the distribution patterns of filtering residuals along each axis, the identification of whether abnormal fluctuations are effectively suppressed, and the display of systematic shifts. Let the original signal be $x_{raw}(n)$ and the filtered signal be $x_{filtered}(n)$. This paper statistically analyzes the residual sequences of the X, Y, and Z axes to demonstrate the processing differences among various methods in terms of signal smoothness.

$$E(n) = x_{raw}(n) - x_{filtered}(n) \tag{11}$$

In the three-axis data from an inertial sensor, the Z-axis typically represents changes in vertical acceleration. During normal walking, the up-and-down foot movements of the human body cause the Z-axis signal to exhibit periodic oscillations. Therefore, the Z-axis signal not only contains rhythm information about human movement but also plays a critical role in step frequency estimation and motion state recognition. If there is significant noise or error in this axis, it will directly affect the accurate judgment of movement rhythm, thereby impacting the estimation accuracy of the entire filtering system. To validate the advantages of the step frequency perception adaptive Kalman filter method proposed in this paper for Z-axis signal processing, the Z-axis of the accelerometer was selected as the primary comparison object, and its error distribution was compared with that of a traditional fixed-parameter Kalman filter.

Figure 2 shows a comparison of the probability density curves of error distributions across the three axes of the accelerometer signal for different methods. Experimental results indicate that the error distribution range of the original signal is the widest, with a longer tail extension, exhibiting obvious fluctuations and occasional abnormal points; while the method proposed in this paper exhibits a more concentrated and symmetrical distribution across all axes, with higher peaks in the error density function and lower dispersion, demonstrating higher signal stability and robustness. Additionally, the Z-axis error decreased by 0.0689 m/s² compared to the fixed Kalman filter.

Figure 3 shows the filtering results of the Z-axis signal from the accelerometer using a fixed-parameter Kalman filter method during the transition from normal walking to fast walking. It can be observed that during the transition to fast walking, the amplitude of the filter output signal changes relatively little, remaining at a level similar to that of normal walking, and thus failing to effectively reflect the change in movement state. This phenomenon indicates that the fixed-parameter Kalman filter lacks dynamic adaptability when faced with significant changes in step frequency, leading to excessive smoothing of transient features in the original signal and thereby suppressing the significant acceleration changes that should be reflected in fast walking. This filter response lag not only weakens the discriminative capability of the Z-axis signal in behavior recognition but may also have negative impacts on downstream sensor-data-based temporal modeling and state estimation. Figure 4 shows the results obtained after processing the Z-axis signal from the accelerometer using the step frequency-aware adaptive Kalman filter method. Compared with the fixed filtering method in Figure 3, the proposed method can sensitively capture the trend of step frequency changes when pedestrians transition from normal walking to fast walking, and dynamically adjust the measurement noise covariance parameters of the filter accordingly, thereby enabling the filter output to better retain the high-amplitude acceleration character-

https://doi.org/10.5194/isprs-archives-XLVIII-4-W14-2025-369-2025 | © Author(s) 2025. CC BY 4.0 License.

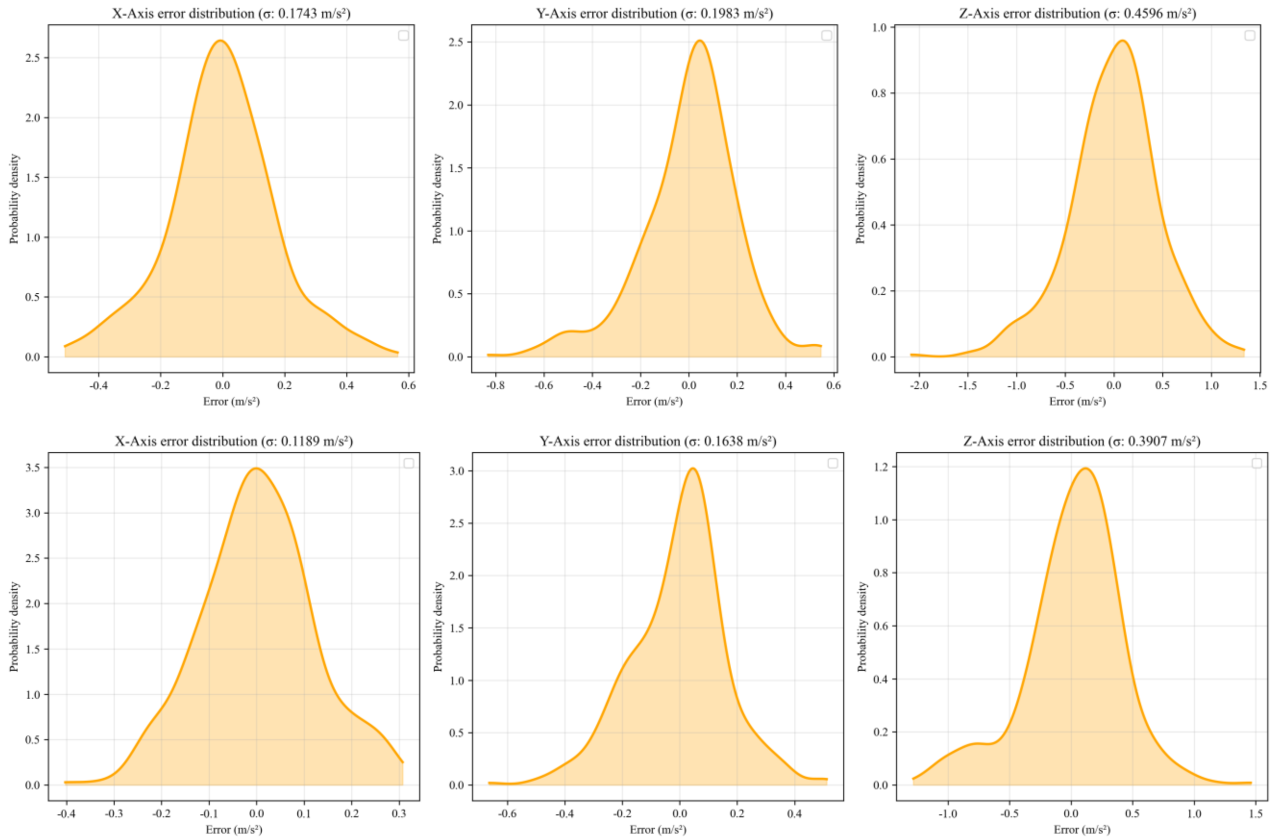

Figure 2. Three-axis error distribution (The top three figures show the three-axis error distribution after fixed Kalman filtering, and the bottom three figures show the three-axis error distribution after adaptive Kalman filtering.).

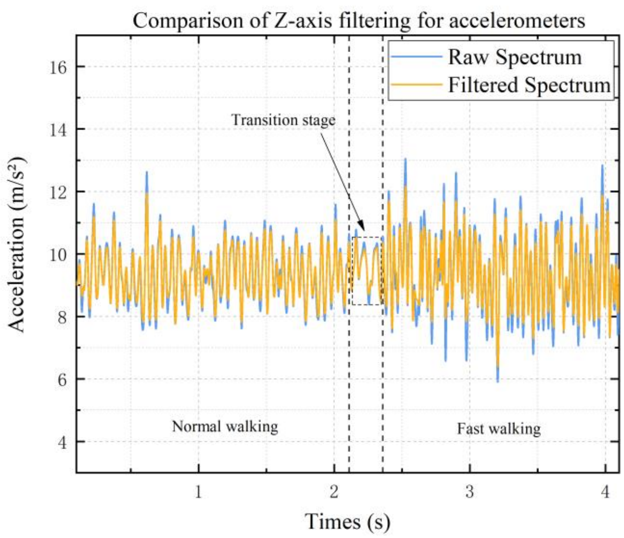

Figure 3. Comparison of raw values and filtered values of accelerometer fixed Kalman filter.

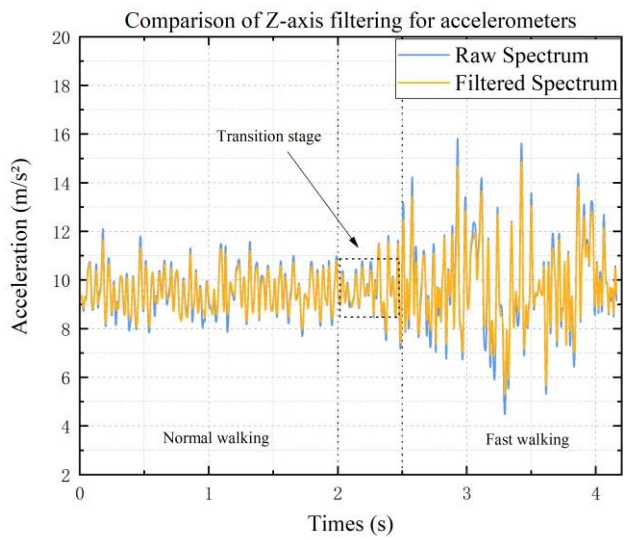

Figure 4. Comparison of raw values and filtered values of accelerometer adaptive Kalman filter.

-istics corresponding to fast walking. Experimental results show that the adaptive filter exhibits greater filtering gain during step frequency increases, reducing suppression of high-frequency signal components and effectively avoiding the “over-smoothing” issue in traditional methods. The proposed method achieves a self-balancing between noise suppression and dynamic response, thereby significantly enhancing the ability to perceive changes in motion states while ensuring signal stability.

To quantify the sensitivity of filters to gait transitions, this paper introduces rise time as an important indicator for evaluating the tracking speed of filters. Rise time is a commonly used time-domain indicator in signal processing and control systems, defined as the time required for the system response to rise from 10% of the low value to 90% of the high value, reflecting the speed and delay of the system response (Li and Jian, 2024):

$$T_r = \frac{t_{90\%} - t_{10\%}}{f_s} \times 1000 \tag{12}$$

In this study, we compared the performance of fixed-parameter Kalman filtering and the method described in this paper in terms of rise time on the Z-axis acceleration signal. The results are shown in Table 2:

Method	T_r
Fixed-parameter Kalman filter	145.6ms
Methodology of this paper	127.0ms

Table 2. Rise Time Comparison.

As can be seen from the data, the average rise time of the proposed method was significantly reduced by 12.8%, indicating that it has a fast filtering response speed in scenarios with sudden changes in step frequency. These experiments demonstrate that the step frequency sensing mechanism effectively improves the time-domain response performance of the filter in real-world walking scenarios by dynamically adjusting the measurement noise covariance, enabling it to avoid over-smoothing while quickly adapting to input changes when capturing signal changes.

Based on the proposed step frequency-aware adaptive Kalman filter method, this paper designs and develops a mobile multi-sensor data acquisition and visualization system on the Android platform. The system uses Android Studio as the development environment and integrates native sensor APIs to achieve real-time acquisition, storage, and filtering of multi-source inertial sensor data. During operation, the system simultaneously displays a comparison line chart of raw data and filtered results. It also integrates a local data export module, enabling the storage of complete multi-dimensional time series data in CSV format. This provides reliable data support for subsequent tasks such as deep learning-based trajectory modeling, behavior recognition, and scene element prediction. Figure 5 shows the system interface.

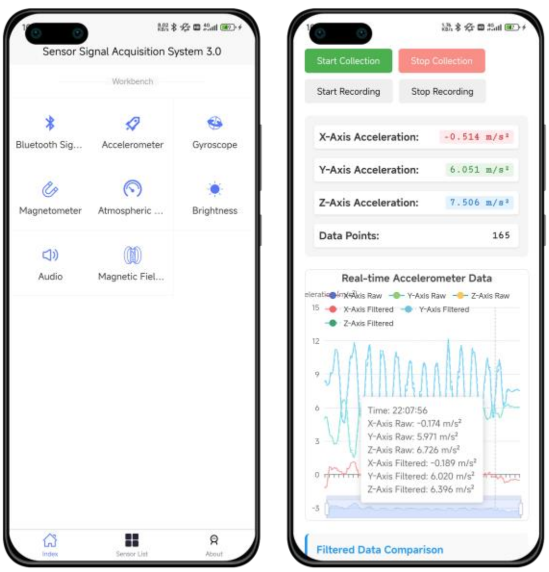

Figure 5. Multi-source data collection software app

5. Conclusion

This paper proposes an adaptive Kalman filter method based on step frequency sensing to enhance the stability and accuracy of multi-dimensional sensor data acquisition in dynamic environments. The method achieves adaptive control of the filtering behavior by dynamically adjusting the measurement noise covariance matrix through real-time analysis of changes in user step frequency, thereby overcoming the issues of slow response to sudden movements and excessive smoothing associated with traditional Kalman filters under fixed parameter conditions. An Android multi-dimensional sensor acquisition system developed based on this method was used to collect and evaluate inertial signals under different gait conditions in real-world scenarios. Experimental results demonstrate that the proposed method offers advantages in terms of signal stability and dynamic response speed.

The adaptability of the current method mainly relies on a single motion feature, namely step frequency, and it still has certain limitations for more complex or non-periodic turning, pausing, and stair climbing motion patterns. In future work, we will expand the identification and modeling of non-periodic motion states, introduce the LSTM algorithm from deep learning into the behavior classification module to judge scene switching, and then dynamically adjust the filter structure.

Future work will focus on the following areas: In the field of deep learning, we will compare mainstream deep learning algorithms to analyze differences in model structure adaptability, feature fusion efficiency, dynamic scene generalization, and computational resource consumption. At the system level, we will further optimize the filtering module and data storage structure to achieve low-power, high-real-time data collection and distribution mechanisms, providing high-quality data support for subsequent tasks such as intelligent indoor positioning, behavior recognition, and semantic map construction.

References

Adžemović, M., Tadić, P., Petrović, A., Nikolić, M., 2024. Beyond Kalman filters: deep learning-based filters for improved object tracking. *Machine Vision and Applications* 36, 20,doi:10.1007/s00138-024-01644-x.

Ghanizadegan, K., Hashim, H.A., 2025. DeepUKF-VIN: Adaptively-tuned Deep Unscented Kalman Filter for 3D Visual-Inertial Navigation based on IMU-Vision-Net, p. arXiv:2502.00575.

Lee, G.T., Seo, S.B., Jeon, W.S., 2021. Indoor Localization by Kalman Filter based Combining of UWB-Positioning and PDR, 2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC), pp. 1-6.

Levy, A., Klein, I., 2025. Adaptive Neural Unscented Kalman Filter, p. arXiv:2503.05490.

Li, E., Jian, J., 2024. Top-Down Design Method of a Time Domain Accelerometer with Adjustable Resolution. *Micromachines (Basel)* 15,doi:10.3390/mi15050635.

Pandey, Y., Bhattacharyya, R., Nath Singh, Y., 2024. Adaptive Invariant Extended Kalman Filter with Noise Covariance Tuning for Attitude Estimation, p. arXiv:2410.01958.

Pang, S., Zhang, B., Lu, J., Pan, R., Wang, H., Wang, Z., Xu, S., 2024. Application of IMU/GPS Integrated Navigation System Based on Adaptive Unscented Kalman Filter Algorithm in 3D

Positioning of Forest Rescue Personnel. *Sensors (Basel)* 24,doi:10.3390/s24185873.

Poulose, A., Han, D.S., 2021. Hybrid Deep Learning Model Based Indoor Positioning Using Wi-Fi RSSI Heat Maps for Autonomous Applications. *Electronics* 10,doi:10.3390/electronics10010002.

Sun, B., Zhang, Z., Qiao, D., Mu, X., Hu, X., 2022. An Improved Innovation Adaptive Kalman Filter for Integrated INS/GPS Navigation. *Sustainability* 14,doi:10.3390/su141811230.

Wu, D., Xia, L., Geng, J., 2018. Heading Estimation for Pedestrian Dead Reckoning Based on Robust Adaptive Kalman Filtering. *Sensors (Basel)* 18,doi:10.3390/s18061970.

Xie, X., Geng, R., Ma, J., Zhou, B., 2025. AKF-LIO: LiDAR-Inertial Odometry with Gaussian Map by Adaptive Kalman Filter, p. arXiv:2503.06891.

Yan, W., Zhang, Q., Wang, L., Mao, Y., Wang, A., Zhao, C., 2020. A Modified Kalman Filter for Integrating the Different Rate Data of Gyros and Accelerometers Retrieved from Android Smartphones in the GNSS/IMU Coupled Navigation. *Sensors (Basel)* 20,doi:10.3390/s20185208.

Yu, C., Haiyong, L., Fang, Z., Qu, W., Wenhua, S., 2020. Adaptive Kalman filtering-based pedestrian navigation algorithm for smartphones. *International Journal of Advanced Robotic Systems* 17, 1729881420930934,doi:10.1177/1729881420930934.

Zhao, H., Cheng, W., Yang, N., Qiu, S., Wang, Z., Wang, J., 2019. Smartphone-Based 3D Indoor Pedestrian Positioning through Multi-Modal Data Fusion. *Sensors* 19, 4554

Zheng, L., Zhan, X., Zhang, X., Wang, S., Yuan, W., 2020. Heading Estimation for Multimode Pedestrian Dead Reckoning. *IEEE Sensors Journal* 20, 8731-8739,doi:10.1109/JSEN.2020.2985025.