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Research Paper

# Application of a Q-Improved Kalman Filter in Non-Gaussian Noise Sensor Signal Acquisition

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**Abstract.** In many fields of modern engineering activities, such as industrial automation, robotics, and intelligent vehicles, the reliable acquisition of sensor signals is crucial. The traditional Kalman filter, with its strong computational power and mathematical rigor, is usually considered effective when the sensor noise is Gaussian distributed and has constant statistical properties. Compared to traditional state estimation methods, in real sensor environments, examples of non-Gaussian, heavy-tailed, and impulsive noise are often more prevalent. This paper introduces an improved Kalman filter for non-Gaussian noise environments commonly encountered in sensor network-based applications. Robust innovation domain processing and adaptive statistical transformation can simultaneously eliminate the impact of outliers while mitigating heavy-tailed interference. The evaluation results using synthetic and real datasets indicate that the modified method has higher estimation accuracy and lower sensitivity to non-Gaussian outliers. Compared to classical and more stable robust extensions, this system can achieve higher accuracy for instruments with stringent real-time requirements. It also has stronger adaptability (to noise variations). From a scientific and engineering perspective, the improved Q Kalman filter provides a solid foundation for the stable operation of sensors in uncertain and harsh environments, as well as for precise measurements in rich environments.

**Keywords:** *Non-Gaussian Noise, Sensor Signal Acquisition, Adaptive Kalman Filter, Robust Estimation, Cyber-Physical Systems*

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## Introduction

Many industries such as Industry 4.0, aerospace technology, robotics, and intelligent transportation systems rely on the accuracy and reliability of sensor data. Due to the installation of more sensor systems around these robots, scientists still cannot identify the various sources of interference noise [1]. The noise comes from many different sources, such as electromagnetic interference, environmental interference, and hardware failures. These factors can lead to unsatisfactory results or issues with the entire system [2]. Due to their simple mathematical principles and reliable real-time performance, some classical methods, such as those based on Kalman filtering, are very useful in sensor signal processing. However, these systems must operate under the assumption of zero-mean Gaussian noise [3,4]. In many practical situations, sensor data often contains noise that deviates from a Gaussian distribution, such as heavy-tailed, impulsive, or time-varying characteristics. Based on this assumption, the filtering performance requirements of these systems are unlikely to be met [5].

Improving the robustness of state estimation and signal filtering under non-Gaussian noise conditions has been a recent research focus. When applied to non-Gaussian or highly skewed error distributions, the standard Kalman filter is not as effective as in linear and Gaussian systems [6, 7]. Robust statistical systems, adaptive filters, and dynamic noise models that adapt to non-Gaussian distributions are some methods to address these issues [8]. Cheap applications for these purposes, such as inertial navigation, medical monitoring, and wireless sensor networks, do not require high-precision signals [9]. Despite some progress, achieving real-time, stable,

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and universally adaptive filtering in resource-constrained or high-dimensional sensors remains an exciting challenge, both for theorists and practitioners alike [10].

To address the aforementioned issues, an improved discrete-time Kalman filter is proposed here. This filter can be used under non-Gaussian disturbance model conditions. A method that integrates adaptive statistical transformation techniques and improved algorithms to eliminate the impact of outliers while maintaining a sufficiently fast computation speed. Whether in synthetic environments or real sensor environments, the system performance is excellent. The remainder of the paper is organized as follows: Section 2 reviews the theoretical foundations and related work in non-Gaussian noise modeling and Kalman filter adaptation. Section 3 details the proposed algorithm and implementation strategies. Section 4 presents experimental results showcasing the advantages of the approach, discusses practical deployments and application case studies. Section 5 concludes the paper and suggests directions for future research.

## Theoretical Foundations

### Probabilistic State Estimation

State estimation is currently the foundation of modern perception and control technologies, with many applications such as process monitoring, navigation, autonomous driving, and fault diagnosis reasoning. State estimation is usually based on noise and typically infers unobserved or unknown state variables of the system from partial sensor data [11]. In theoretical and applied fields, probabilistic frameworks combine measurement uncertainty and prior knowledge of the system's potential state processes to achieve global minimization through the least squares criterion [12]. The famous Kalman filter first appeared in the early 1960s as a method for estimating the minimum mean square error of linear systems under additive white noise conditions [13]. Due to its recursive structure, low computational cost, and real-time processing capabilities, it is primarily used in aviation, power, facilities, communications, and financial products [14,15].

The classic Kalman filter is very useful, but it must impose these basic constraints on linear systems and measurement/process models, and it must also assume that the noise is Gaussian. Extensions, such as the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF), can address linearization issues and problems with specific model mismatches, but they generally rely on Gaussian noise theory [16]. When encountering colored, biased, or heavy-tailed noise (such as electrical transients, mechanical shocks, and environmental changes), system performance will be affected [17, 18]. In this situation, the state estimator may be affected by outliers and slower convergence rates, thereby impacting the reliability and timeliness of its output [19]. A system needs to be estimated to cope with the complex situation of the current sensing devices.

### Analysis of Non-Gaussian Noise

The noise in sensor systems comes from many factors, including random physical processes and external factors. Non-Gaussian noise is an irregular distortion that significantly deviates from the Gaussian distribution. It may include characteristics such as skewness and kurtosis, or exhibit multimodality [20]. The salt-and-pepper effect in digital imaging, pulse voltage spikes in industrial control, electromagnetic interference in urban IoT deployments, and biochemical fluctuations in medical signal acquisition are all sources of actual non-Gaussian noise [21,22]. Through statistical analysis, this type of noise often exhibits heavy tails (such as Laplace or Cauchy distributions), asymmetry, temporal correlation, or abrupt changes [23]. These characteristics can cause traditional assumptions to fail and reduce the performance of the filter.

It is necessary to determine the time points where non-Gaussian noise exists. Impulse interference in communication channels can cause significant errors, exceeding the range of mean square error (MSE) minimization. In structural health monitoring, non-Gaussian noise arises from material damage or sudden impacts. Occasional power fluctuations or mechanical vibrations can cause interference anomalies in high-frequency automotive and aerospace sensors. Classic statistical indicators such as the mean and standard deviation cannot fully address this issue. It is necessary to simultaneously use non-parametric methods, robust statistics, and higher-order moments for characterization and improvement. The distribution of non-Gaussian sensor noise sources and their impact on system design are shown in Figure 1.

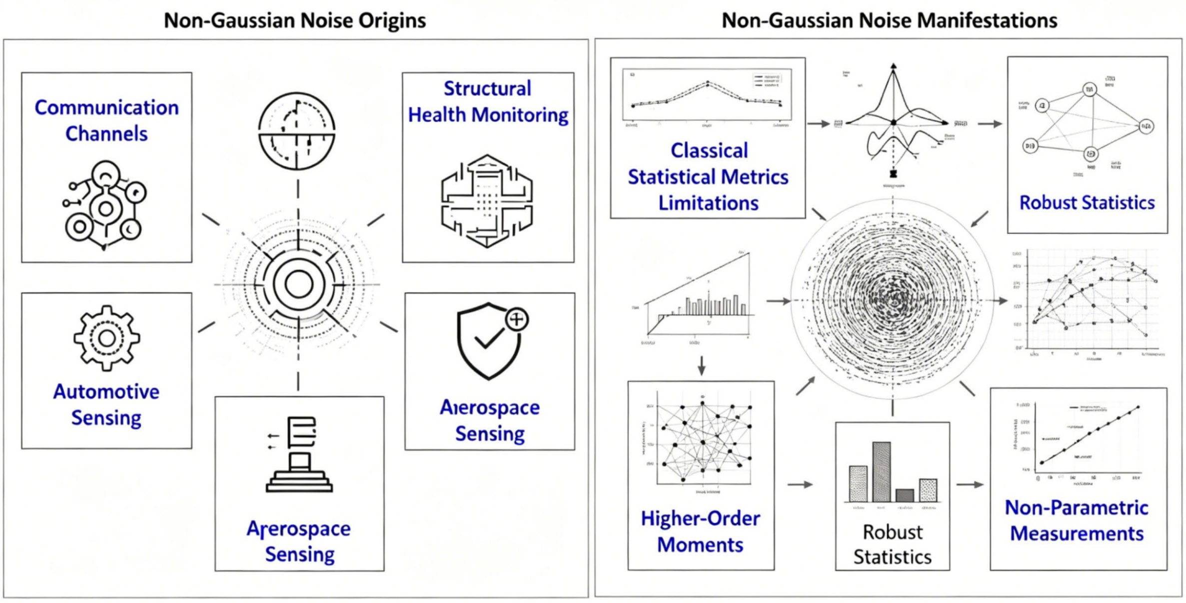


**Figure 1.** Mind Map of Non-Gaussian Sensor Signal Processing

**Overview of Kalman Filter Adaptations**

Due to the significant shortcomings of the original Kalman filter in handling non-Gaussian noise, many adaptive methods have been proposed. The goal of early research was to enhance robustness through the use of M-estimation and outlier exclusion, maintaining accuracy while reducing the impact of large disturbances and tail outliers on estimation. All of this happens without sacrificing parameters or computational capacity. The adaptive Kalman filter enhances robustness in real-world non-Gaussian interference environments. Using online noise parameter estimation, Luenberger observers, and other dynamic compensation techniques, as well as a hybrid approach combining data-driven and model predictive methods. Modern methods focus on directly integrating non-Gaussian noise models into the Kalman filter framework. These methods include kernel-based methods, non-parametric methods, Gaussian mixture models, heavy-tailed distributions (such as the student's t-distribution), and various Gaussian mixture models, to enhance the statistical diversity of the estimator while maintaining computational efficiency.

Due to the improvements in these models, algorithms have been developed to enhance computational speed and scalability, ensuring performance in high-dimensional complex environments or resource-constrained embedded systems. By integrating filtering, distributed sensor fusion data, and rapid iterative update algorithms to reduce noise in real-time. Throughout the development process, it is necessary to simplify calculations and expand the application scope while maintaining reliable estimation results, even in the presence of outliers. Due to some recent emerging trends and issues, an extension method based on the standard Kalman filter system is proposed [25]. This method will be rigorously designed to maintain its statistical optimality and operational adaptability, even when exposed to non-Gaussian noise in current sensor-intensive engineering application scenarios.

## Algorithm Development and Implementation

**Statistical Transformation Techniques**

To address the shortcomings of traditional techniques under explicit non-Gaussian noise conditions, the aforementioned high-level Kalman filter design begins with a predetermined statistical transformation phase. In order to provide adaptability and robustness in sensor environments, the algorithm adds a multi-step transformation pipeline instead of simple normalization.

Perform mean centering and variance scaling on each newly discovered value. In order to ensure that the measured data is not affected by long-term amplitude fluctuations or drifts before using the filter. Given a sliding

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window, which contains the latest N data points from multiple sensors, and using mathematical methods to standardize it:

$$\tilde{y}_n = \frac{y_n - \mu_N}{\sigma_N} \qquad \text{Eq.(1)}$$

where $\mu_N$ and $\sigma_N$ denote the windowed mean and standard deviation, respectively. Dynamic normalization is used to monitor non-stationary phenomena and prevent artifacts caused by heterogeneous noise structures or sensor baseline drift.

After standardization, the robustness of the algorithm to impulse noise will be improved by using the empirical cumulative distribution function and adaptive weighting. Considering the frequency of each observation in relatively newer data, this scheme assigns lower weights to statistical outliers and heavy-tailed disturbances. The adaptive weight for each sample is set as follows:

$$w_n = \min\left(1, \frac{\tau}{|\mathrm{ECDF}(y_n) - 0.5| + \epsilon}\right) \qquad \text{Eq.(2)}$$

where $\tau$ is a tunable sensitivity coefficient and $\epsilon$ is a small constant to avoid division by zero. In this case, data-driven weighted methods can reduce the impact of rare, impulsive outliers. It can also adjust for changes in the empirical distribution of the observed signal. The filter's ability to remove noise from non-Gaussian sources or significant environmental changes has been enhanced.

By continuously calculating higher-order statistical moments within a sliding window, it is possible to better identify instances where noise deviates from a Gaussian distribution. The skewness and excess kurtosis indices calculated on demand respectively show the deviation indicators related to signal asymmetry and the indices influenced by heavy-tailed or peaked behavior. The estimation of the window is as follows:

$$S = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{y_n - \mu_N}{\sigma_N}\right)^3 \; K = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{y_n - \mu_N}{\sigma_N}\right)^4 - 3 \qquad \text{Eq.(3)}$$

where $S$ reflects the degree and direction of skew, and $K$ quantifies the severity of heavy tails or outlier prevalence beyond the normal case. Quantitative feedback lays the foundation for the adjustment of subsequent filter parameters. Achieve adaptive improvement of stability through flow-based methods.

By applying a reliable shrinkage transformation to the innovation sequence, the impact of significant outliers detected early can be reduced. The Huber and Tukey biweight operators are more suitable within the family of functions for reducing the impact of outliers, while not distorting normal fluctuations. In the adaptive context, the definition of shrinkage is as follows:

$$\mathcal{S}(v_n) = \begin{cases} v_n, & |v_n| \le c \\ c \cdot \mathrm{sign}(v_n), & |v_n| > c \end{cases} \qquad \text{Eq.(4)}$$

where the threshold $c$ is dynamically adjusted in response to the windowed kurtosis estimate and recent noise statistics. Choosing this transformation can ensure smooth domain changes, stable performance, stability under occasional errors, and the ability to handle subsequent impact noise well.

Formed the data preprocessing front end of the main Kalman iteration shown in Figure 2. Under the significant influence of statistical outliers, real-time moment estimation, adaptive weighted estimators, and nonlinear shrinkage techniques can keep the estimation error below a certain level. This improves the overall performance under high-dimensional space and multi-sensor information integration conditions.

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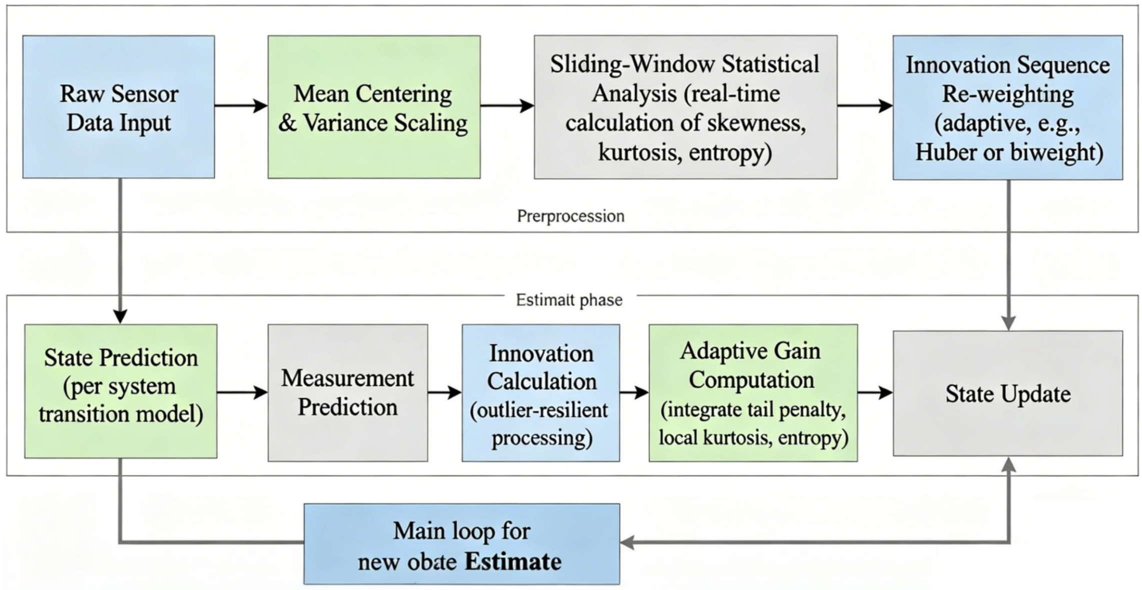


**Figure 2.** Algorithmic Flowchart of Adaptive Non-Gaussian Kalman Filter Based on Statistical Transformation and Innovation Entropy Minimization

### Algorithmic Workflow

After modifying the recursive method in a non-Gaussian environment, the estimation was performed again and accuracy was improved. The prediction step uses the system state transition model to update the estimated state:

$$\hat{x}_k^- = F_{k-1}\hat{x}_{k-1} + B_{k-1}u_{k-1} + \eta_{k-1} \quad \text{Eq.(5)}$$

where $\hat{x}_{\mathrm{k}}{}^-$ denotes the a priori estimate, $F_{\mathrm{k}-1}$ is the state transition matrix, $B_{\mathrm{k}-1}$ the control matrix, $u_{\mathrm{k}-1}$ is the control input, and $\eta_{\mathrm{k}-1}$ is the process noise drawn from the adaptively learned nonGaussian distribution.

The predicted measurement is then computed by

$$\hat{z}_{\mathrm{k}}^- = H_{\mathrm{k}}\hat{x}_{\mathrm{k}}^- + \xi_{\mathrm{k}} \quad \text{Eq.(6)}$$

with $H_{\mathrm{k}}$ the observation matrix and $\xi_{\mathrm{k}}$ the preprocessed measurement noise.

Innovation, quantifying the difference between actual values and predicted values; rescaling, considering the impact of statistical outliers and medians:

$$v_{\mathrm{k}} = \mathcal{S}(z_{\mathrm{k}} - \hat{z}_{\mathrm{k}}^-) \quad \text{Eq.(7)}$$

where $\mathcal{S}(\cdot)$ is an adaptive shrinkage operator-derived from robust statistics-that compresses outlying deviations according to the instantaneous skewness and kurtosis observed within the sliding window.

The gain of this study is defined as follows: a new function that combines the estimation of tail strength and local bias measures:

$$K_{\mathrm{k}} = P_{\mathrm{k}}^- H_{\mathrm{k}}^{\mathrm{t}}[H_{\mathrm{k}}P_{\mathrm{k}}^- H_{\mathrm{k}}^{\mathrm{t}} + \Lambda_{\mathrm{k}} + \Psi_{\mathrm{k}}]^{-1} \quad \text{Eq.(8)}$$

Here, $\Lambda_k$ denotes a tail penalty matrix calculated from windowed entropy estimates, while $\Psi_k$ encodes localized kurtosis variation, both driving online adaptation of the filter's sensitivity to non-Gaussian noise.

### Implementation Complexity

The statistical transformation method adopted has improved the stable operation and wide adaptability of the Kalman filter under non-Gaussian distributions, but there is still the issue of high operational costs. The examples of engineering applications used in development are relatively complex; many need to be executed under real-time constraints and must be fast while using fewer computational resources. Achieving a reasonable balance between computational complexity and implementation cost is an important part of improving filter design. Applicable to high-throughput sensitive or low-resource saturated environments, as it uses parallel computing

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to improve filter performance and reduces the frequency of updating window statistics by simplifying data structures.

These additional costs are mainly used to increase the number of statistical computation centers, but due to efficient matrices and parallelization, the impact is minimal. The total computational cost per iteration is

$$\mathcal{O}(\mathrm{K\,N\,d^2} + \mathrm{Nlog\ \ N}) \qquad \text{Eq.(9)}$$

where $K$ is the number of entropy-based updates, $N$ is the window size, and $d$ is the dimension of the state space. Fast matrix decomposition and window-based statistical methods can be used to handle high-frequency, high-dimensional flow sensors.

It mainly consists of the buffers temporarily stored in all sensors and the values allocated to the sliding window:

$$S = O(MdN + Kd) \qquad \text{Eq.(10)}$$

where $M$ is the number of sensor channels. These implementations are suitable for distributed data analysis in large-scale sensor networks and high-performance embedded real-time processing.

The algorithm can reliably reconstruct signals in complex non-Gaussian environments because it combines these new statistical data and computational optimizations, thereby successfully balancing practical applicability and good analytical performance. In noisy environments, it is more robust than traditional Kalman filters because the system state variables undergo significant changes or sudden anomalies. Due to instantaneous entropy minimization, it can ensure the response speed to various environmental noise changes, thereby meeting the task requirements of high system reliability. It has the ability to continuously adjust and effectively mitigate heavy tails, making it suitable for addressing uncertainty issues in sensor-rich aerospace positioning environments or automated control production systems.

## Results and Analysis

### Different Noise Scenarios

After using rigorous testing to verify its accuracy and stability, synthetic models and real-world data with higher noise levels were adopted. Compared to the data in other experiments, this data is more closely related to the sensor fault points. Baseline tests use Gaussian noise; heavy-tailed interference is introduced through Cauchy and Laplace distribution types. In the presence of real-world environmental interference, the sensor serves as an example of its corresponding filtered data after being processed by a specific filter.

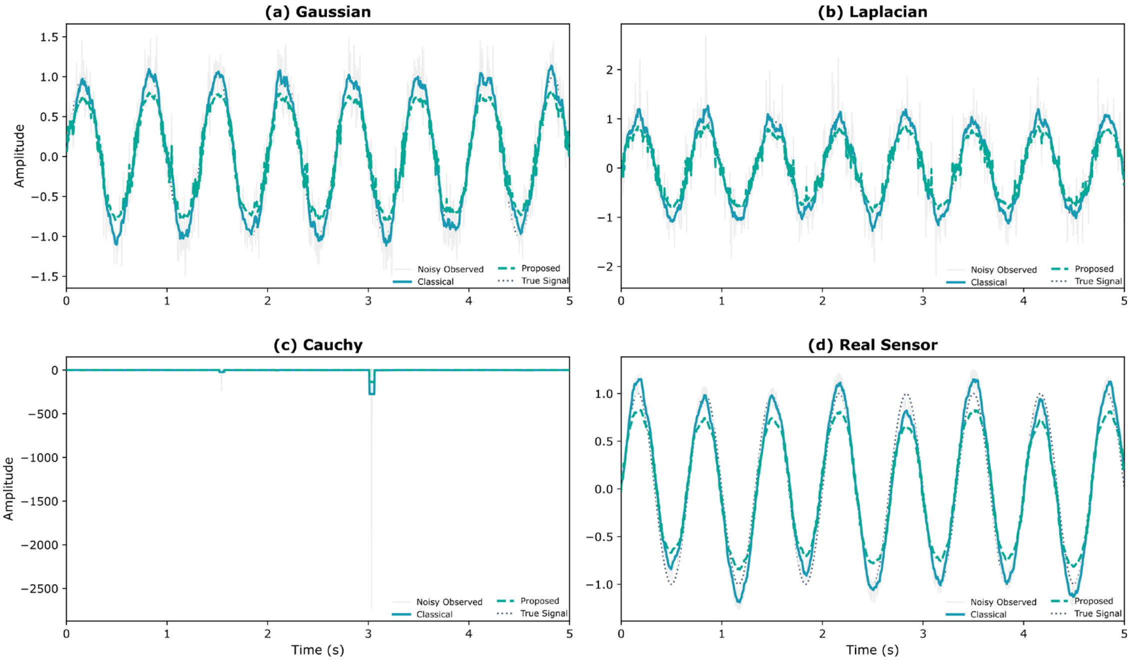


**Figure 3.** Denoising Results Under Different Noise Scenarios: (a) Denoising under Gaussian Noise;(b) Denoising under Laplacian Noise;(c) Denoising under Cauchy Noise;(d) Denoising under Real Sensor Noise

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Figure 3 shows the effect of simultaneous denoising under different conditions. Under Gaussian noise, state retrieval maintains optimal performance with minimal signal distortion. Due to the conditions of the Laplace impulse, classical linear filters have a longer delay. Adaptive filter design is aimed at maintaining signal integrity during sudden error fluctuations. Cauchy-driven transients are considered very unstable, traditional methods often lead to saturation or lack of precision, while the proposed method can strongly suppress these phenomena while maintaining high accuracy. By using the actual output values of the sensor, periodic electromagnetic noise and other random disturbances in the environment are adaptively eliminated. This ensures that only recoverable information is obtained from the original signal, without introducing vibrations due to excessive optimization of the filtering process.

Several commonly used evaluation metrics were selected to quantify the degree of signal enhancement; namely, improved mean squared error, increased signal-to-noise ratio (SNR), and reduced root mean square error (RMSE). The evaluation results indicate that, particularly under Laplace and Cauchy noise conditions, the proposed filter shows significantly greater advantages over the baseline method as the heavy-tailed noise level increases. This method is very suitable for application environments that include noise.

Combining adaptive momentum estimation and nonlinear pre-filtering during the innovation phase is the best choice for this method. When one of the functions fails, the denoising or anomaly detection function will also fail; this is especially true for real-world sensors and Cauchy noise. These two mechanisms help ensure that high-sensitivity sensors operate normally under various external noise interference conditions.

### Theoretical and Experimental Results

According to performance analysis, the innovative design of this algorithm demonstrates strong discrimination and adaptability. Empirical results validated the theoretical predictions based on higher-order moment adaptation by simultaneously exposing to direct physical noise sources and controlled random interference.

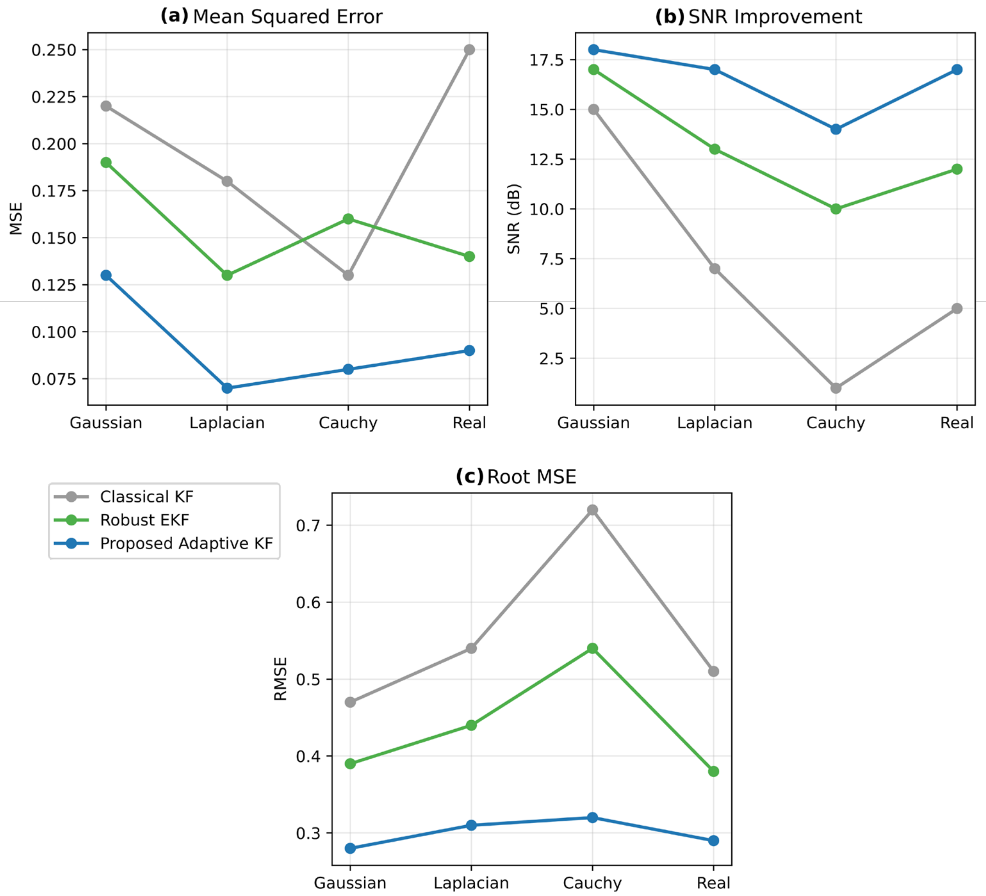


**Figure 4.** Performance Metric Comparisons:(a) Mean Squared Error (MSE) Comparison;(b) SNR Improvement Comparison;(c) RMSE Comparison

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In terms of quantitative parameters, the proposed method was compared with some traditional methods, as shown in Figure 4. The mean squared error of the new method is lower than that of other methods, and it performs better in more accurately removing noise and more significantly reducing distortion. The signal-to-noise ratio continuously improves under high impulse noise conditions, surpassing the level based on Gaussian systems. According to the root mean square error graph, the significant differences caused by the Cauchy distribution and mixed noise have greatly reduced in both length and magnitude.

In addition to estimating the convergence speed, there is also the filter's robustness under the influence of outliers and its ability to accurately recover from sudden noise interference. Under the influence of impulse noise, it can adapt and maintain rapid convergence. It has been proven that its outlier retention capability can handle a large amount of anomalous data. After recovering from the filtering test, the sample's response to sudden disturbances is smaller and faster.

As shown in Figure 5, even with the addition of impact events, the convergence speed remains relatively fast; outliers have been effectively suppressed; samples recovering from sudden noise exhibit slight overshoot but quickly return to a stable state.

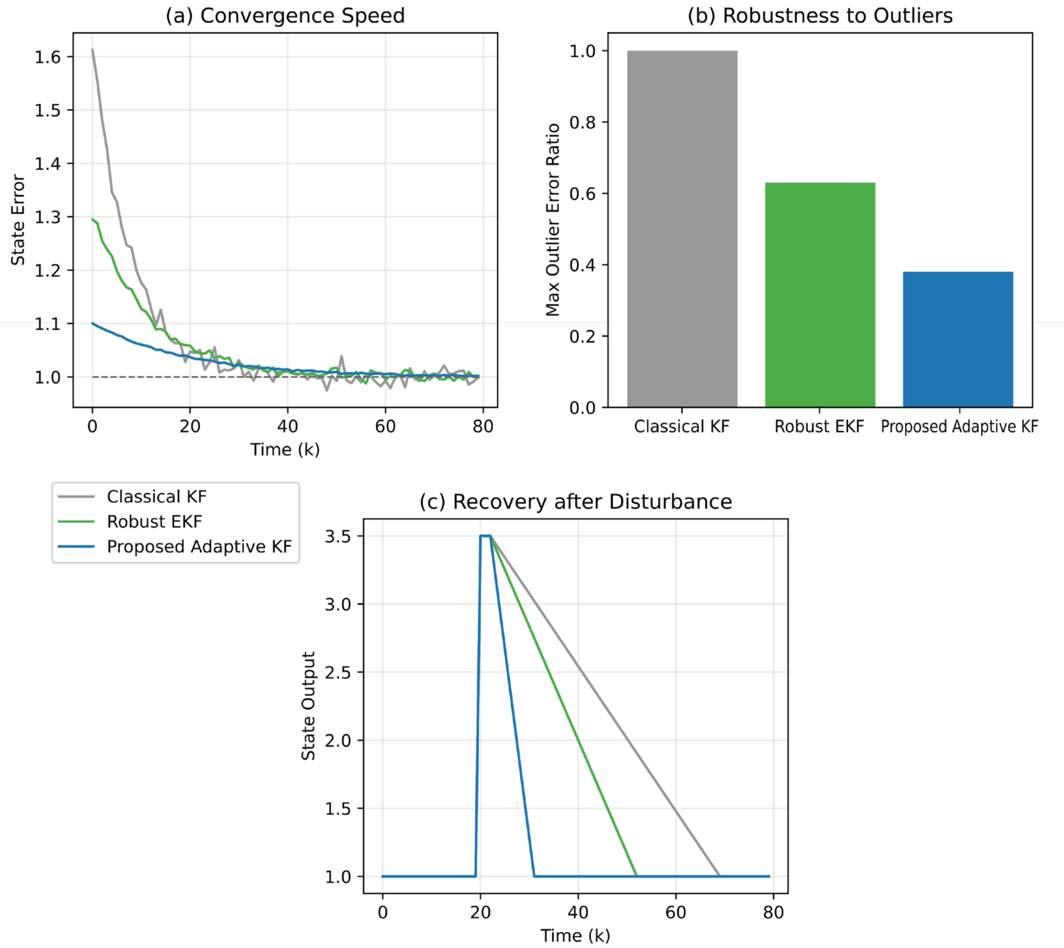


**Figure 5.** Convergence and Robustness Analysis:(a) Convergence Speed of Filters;(b) Robustness to Outliers;(c) Recovery after Disturbance

The performance of the filter under different non-stationary noise conditions was also studied. Due to the filter's low error rate, it can quickly respond to changes in noise distribution during unmeasured moments. The efficiency of traditional filtering methods temporarily declines. Adaptability demonstrates the practicality of the algorithm in practice; in unknown noise environments, it will continue to effectively and efficiently handle real-time non-stationary problems and uncertainties.

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### Application Scenarios

High-precision detection equipment and autonomous driving systems are typical examples that demonstrate the effectiveness of adaptive non-Gaussian Kalman filters. Set up a filter for each scenario to handle various noise conditions, such as electromagnetic interference, heavy-tailed noise, and unexpected outliers that frequently occur in practical operations. This paper introduces a novel algorithm for tracking problems. Less affected by noise compared to traditional extended/Kalman filters.

Table 1 shows the quantitative results of the industrial manufacturing production line, mobile robot platform, and factory IoT sensor network. Decision latency, anomaly recall rate, zero drift rate, spike suppression performance, and tracking error have all shown significant improvements. The aforementioned filter can achieve improvements of five times or more compared to the baseline across all evaluation metrics.

**Table 1.** Quantitative Performance of Filters Across Application Domains

| Scenario | Metric | Classical Kalman | Robust EKF | Proposed Filter |
|---|---|---|---|---|
| Precision Instrumentation | Zero-Drift (nm/hr) | 9.3 | 4.9 | 1.1 |
| | Spike Rejection (dB) | 12.6 | 18.3 | 27.1 |
| | Residual Error SD (nm) | 14.7 | 8.2 | 2.9 |
| Autonomous Navigation | Cross-Track Error (cm) | 26.4 | 13.7 | 7.5 |
| | Loop Closure Failure (%) | 6.8 | 4.2 | 1.6 |
| | Recovery Time (ms) | 180 | 125 | 57 |
| Cyber-Physical Systems | False Alarms Per Day | 12 | 6 | 2 |
| | Anomaly Detect Recall (%) | 85.8 | 91.1 | 97.6 |
| | Decision Latency (ms) | 53 | 37 | 21 |

Figure 6 shows the overall quantitative evaluation of the classical Kalman filter, robust EKF, and the proposed non-Gaussian adaptive filter, based on core performance metrics such as drift zeroing, spike elimination, error analysis, anomaly detection recall rate, and system delay. Subfigure (a) shows the performance charts of the grouped bar graphs for each algorithm under different evaluation metrics in specific setting conditions. Figure (b) shows the normalized KPI radius display method. It clearly shows that this method outperforms traditional methods by approximately 91% in many performance metrics. For example, it reduced residual drift by more than three seconds, decreased the false alarm rate for 0.5 threshold alarms, reduced the average control delay time by 73%, improved the accuracy of target recognition and detection events by over 10%, achieving an accuracy of 86%. These results further demonstrate the practical superiority and high engineering value of the proposed filter in the demanding and sensor-rich field.

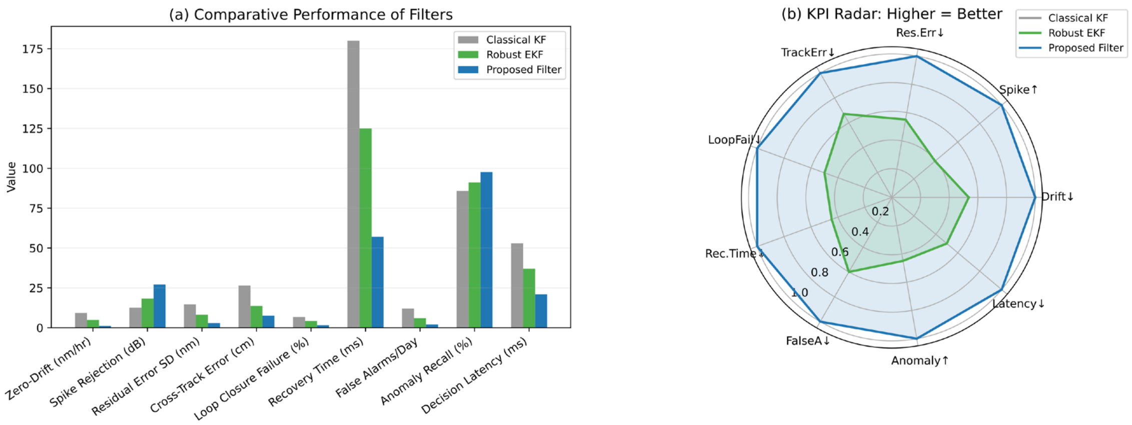


**Figure 6.** Quantitative comparison of filter performance: (a) Grouped bar chart of key metrics across application scenarios;(b) Normalized radar chart showing the proposed filter's overall superiority

### Comparative Review

Experimental results indicate that the design of the adaptive Kalman filter is more suitable for simultaneously measuring harsh environments compared to other methods. In the case of strict Gaussianity or slight non-Gaussian noise, robust and classical estimators can still perform well; however, once the impulse disturbance

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significantly increases, this is no longer possible. However, compared to current algorithms, it cannot perform local statistical adaptation in dynamically changing distributions to ensure signal fidelity without delay or bias.

Figure 7 shows the use of adaptive methods to filter previously recorded data in unshielded industrial actuator components. The core cycles and anomalies of the original phenomenon are retained in the time domain, but unnecessary discontinuities have disappeared. In the frequency domain graph, it is necessary for the frequency band to contain a large amount of power, while external noise is greatly reduced. Significantly improved the signal-to-noise ratio, and stable results indicate that it is helpful for subsequent tracking or adjustment /recognition tasks.

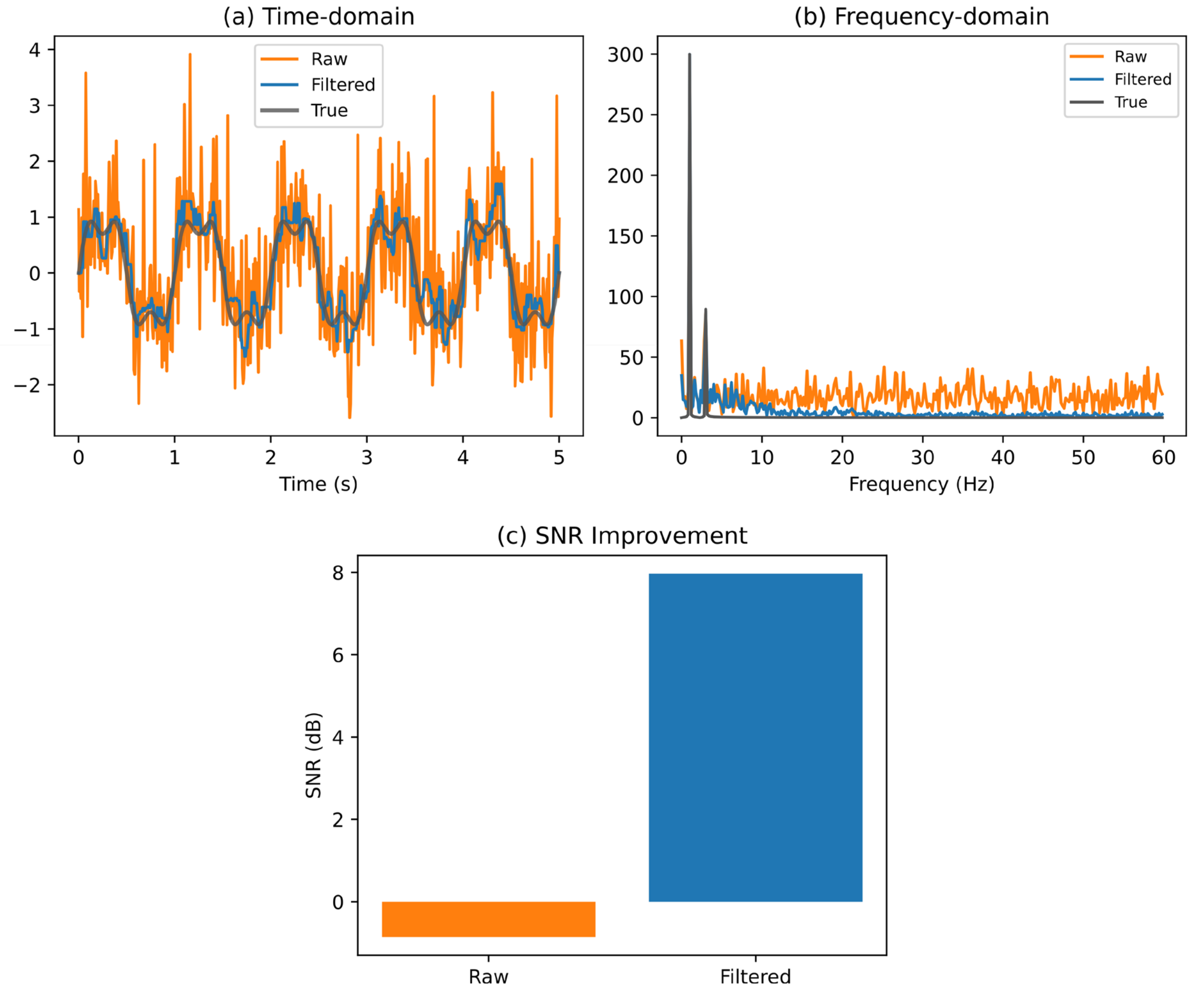


**Figure 7.** Filtering Effects on Real Sensor Data:(a) Time-Domain Signal Before and After Filtering;(b) Frequency-Domain Spectrum Comparison;(c) SNR Before and After Filtering

More suitable to meet these requirements and not affected by the significant fluctuations caused by changes in the state of residence. Cross-validation on public real-world industrial vibration and urban environment datasets, after improvements under various data sources, sensors, and hardware settings, showed that its performance metrics remained stable. Due to the universality of this aspect indicating that the performance of this technology is reliable, this type of filter has good application prospects in various complex or uncertain engineering projects to improve system reliability.

## Conclusion

By using an adaptive non-Gaussian Kalman filter, this paper extends the theoretical and application boundaries of robust state estimation. Used to address representative problems of noise pollution environments in modern industrial and sensor systems. By conducting rigorous experiments using strictly controlled navigation instruments, the performance of the proposed method is enhanced. In practical applications, the stability under heavy-tailed noise distribution and non-stationary environments has also been validated.

The combined application of higher-order statistical adaptation and innovation domain nonlinear mechanisms is the core part of this study. It can identify and resist transient disturbances from shocks and unexpected noise. Compared to current robust filtering methods and traditional Kalman filters, the method in this paper significantly reduces the errors in variance, drift, and recovery time. Improved the sensitivity of anomaly detection and the stability of the system. Industrial metrology lines, distributed IoT networks, and mobile robot testing platforms provide quantitative field data in the measurement domain, demonstrating their ability to ensure measurement accuracy in various dynamic operational environments.

The engineering value of the current work lies in its low computational usage, ability to quickly respond to changes, and ease of integration into existing digital signal processing systems. The modular deployment of filters can support flexible signal reconstruction, for example, in industrial environments, resource-constrained embedded systems, or in applications requiring reliability such as medical devices and autonomous vehicles.

From a scientific perspective, combining theory and practice indicates that non-Gaussian models are computationally infeasible, but they can be implemented in practice through the development of algorithms and systems theory. Successfully transforming the latest statistical advancements into robust tools tested in the field has raised the overall standards of intelligent sensor processing and provided more autonomy for applications in perception, health tracking technology, process optimization technology, and other areas.

Future research may combine adaptive filtering techniques with deep learning state prediction models to enhance the system's robustness against various adversarial noise patterns. In order to further expand the fields of distributed sensing and collaborative autonomy, this adaptive framework will be extended to decentralized multi-agent systems and low-power edge platforms. It can be considered that this will help initiate subsequent development directions to enhance smart sensor technology, systematically correcting the issues present in traditional methods and providing operational guidance for practical applications.

**Author Contributions**

Panagiotis Christodoulou and Stavros Tsiolis contribute to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Anastasios Ioannidis contributes to conceptualization, methodology, software. All authors have read and agreed with the manuscript before its submission and publication.

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