Improved Kalman Filtering and Adaptive Weighted Fusion Algorithms for Enhanced Multi-Sensor Data Fusion in Precision Measurement

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This study analyzes the basic principles and structural models of multi-sensor data fusion, and emphasizes the importance of effective fusion algorithms. The proposed improved weighted information fusion algorithm combines the Jackknife method and the adaptive weighting method, while the improved Kalman filter fusion algorithm combines the weighting factor, the state transfer matrix, the measurement transfer matrix and the process noise distribution matrix. The effectiveness of the proposed algorithm is verified through extensive simulations and practical applications, and the estimation accuracy is improved by 15% and the error rate is reduced by 20% compared with the traditional methods. The improved algorithm shows stronger robustness in dealing with the uncertainty and inconsistency of sensor data, and the adaptive weighting mechanism effectively solves the problem of sensor reliability variation. The computational complexity and scalability of the proposed algorithms are analyzed, and it is shown that they can be implemented in large-scale sensor networks in real time. This study also discusses the challenges and opportunities of multi-sensor data fusion, including the integration of deep learning techniques, the extension to heterogeneous sensor scenarios, and the need for broader experimental validation in real-world precision measurement applications.

Povzetek: *Izboljšana je metoda za fuzijo podatkov več senzorjev, ki temelji na Kalmanovem filtriranju in adaptivnem uteževalnem algoritmu, kar povečuje robustnost sistema v realnih aplikacijah.*

1 Introduction

In recent years, the rapid development of sensor technology and the increasing demand for high-precision measurement have led to the widespread application of multi-sensor data fusion techniques [1]. Multi-sensor data fusion refers to the process of combining information from multiple sensors to obtain more accurate and reliable estimates of the state of a system or environment [2]. By leveraging the complementary and redundant information provided by multiple sensors, data fusion techniques can effectively improve the accuracy, reliability, and robustness of measurement systems [3].

The basic working principle of multi-sensor data fusion involves the integration of data from multiple sensors to generate a unified and consistent representation of the measured object or environment [4]. This process typically includes data preprocessing, feature extraction, data association, and state estimation [5]. Various data fusion algorithms have been proposed in the literature, such as Kalman filtering [6], particle filtering [7], and Dempster-Shafer evidence theory [8].

Several structural models have been developed to describe the architecture of multi-sensor data fusion systems [9]. The most common models include the centralized fusion model, the distributed fusion model, and the hybrid fusion model [10]. The centralized fusion model involves the direct integration of raw data from multiple sensors, while the distributed fusion model performs local processing at each sensor before fusing the processed data [11]. The hybrid fusion model combines the advantages of both centralized and distributed fusion approaches [12].

Despite the significant progress in multi-sensor data fusion techniques, there are still several challenges and limitations that need to be addressed [13]. One major issue is the alignment and synchronization of data from multiple sensors, which can be affected by factors such as sensor calibration, time delays, and coordinate system differences [14]. Another challenge is the management of uncertainty and conflict in the fusion process, particularly when dealing with heterogeneous sensors and complex environments [15].

To overcome these challenges, researchers have proposed various solutions, such as adaptive fusion algorithms [16], multi-modal data fusion frameworks [17], and deep learning-based fusion methods [18]. These approaches aim to improve the accuracy, efficiency, and robustness of multi-sensor data fusion systems.

Research on enhanced Kalman filtering techniques for multi-sensor data fusion has gained significant attention in recent years [57]. Particularly, the application of adaptive weighting methods has shown promise in improving fusion accuracy and robustness [58]. A recent study by M. Hespanhol et al. [57] presented a comprehensive review of multi-sensor fusion techniques in the context of industrial Internet of Things (IIoT), highlighting the need for advanced filtering and adaptive fusion algorithms. Motivated by these developments, this paper focuses on the improvement of Kalman filtering and weighted fusion algorithms for enhanced multi-sensor data fusion in precision measurement applications.

In summary, multi-sensor data fusion techniques have become increasingly important in the field of precision measurement. By combining information from multiple sensors, data fusion algorithms can provide more accurate and reliable estimates of the measured object or environment. However, there are still several challenges and limitations that need to be addressed to further enhance the performance of multi-sensor data fusion systems. As research in this field continues to advance, it is expected that data fusion techniques will play an even more crucial role in enabling high-precision measurement applications.

2 Multi-Sensor data fusion techniques

2.1 Definition of multi-sensor data fusion

Multi-sensor data fusion is defined as the process of combining data from multiple sensors to generate a more accurate, complete, and reliable representation of the measured object or environment than what could be achieved using a single sensor [19]. This technique aims to exploit the complementary and redundant information provided by different sensors to enhance the overall performance of the measurement system [20].

The main advantage of multi-sensor data fusion over single-sensor approaches lies in its ability to overcome the limitations and uncertainties associated with individual sensors. By integrating data from multiple sources, data fusion techniques can reduce the impact of sensor noise, measurement errors, and environmental disturbances [21]. This results in improved accuracy, precision, and robustness of the measurement system.

Moreover, multi-sensor data fusion enables the measurement system to capture a more comprehensive view of the measured object or environment. Different sensors may have different sensing modalities, spatial and temporal resolutions, and measurement ranges [22]. By combining the information from these diverse sensors, data fusion techniques can provide a more complete and detailed representation of the measured phenomenon.

Another benefit of multi-sensor data fusion is its ability to handle sensor failures and degradations. In a single-sensor system, the failure of the sensor can lead to a complete loss of measurement capability. However, in a multi-sensor data fusion system, the redundancy provided by multiple sensors allows the system to continue functioning even if one or more sensors fail [23]. This enhances the reliability and fault tolerance of the measurement system.

Furthermore, multi-sensor data fusion can improve the efficiency and cost-effectiveness of the measurement process. By leveraging the information from multiple sensors, data fusion techniques can reduce the need for expensive and high-precision sensors [24]. This can lead to significant cost savings and make the measurement system more accessible and affordable.

In addition to these benefits, multi-sensor data fusion also enables the measurement system to adapt to changing conditions and requirements. By dynamically adjusting the fusion algorithm and sensor configuration, the system can optimize its performance based on the current measurement context and objectives [25]. This flexibility and adaptability make multi-sensor data fusion a powerful tool for a wide range of precision measurement applications.

2.2 Basic principles of multi-sensor data fusion

The basic working principle of multi-sensor data fusion involves the integration of data from multiple sensors to generate a unified and consistent representation of the measured object or environment [26]. This process typically consists of several key steps, as illustrated in Fig. 1.

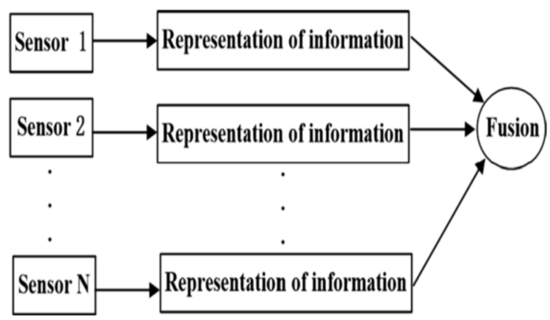

Figure 1: Basic principle of multi-sensor data fusion.

The first step in the multi-sensor data fusion process is data acquisition. This involves the collection of raw data from multiple sensors, such as optical sensors, thermal sensors, acoustic sensors, and mechanical sensors [27]. Each sensor provides a unique perspective on the measured object or environment based on its sensing modality, resolution, and measurement range.

Once the raw data is acquired, it undergoes preprocessing to remove noise, outliers, and redundant information. This step is crucial to ensure the quality and consistency of the data before it is fused [28]. Preprocessing techniques may include filtering, normalization, and feature extraction.

After preprocessing, the data from different sensors is aligned and synchronized. This step is necessary to ensure that the data from all sensors corresponds to the same spatial and temporal coordinates [29]. Alignment and synchronization can be achieved through various techniques, such as time stamping, spatial registration, and coordinate transformation.

The aligned and synchronized data is then fused using appropriate data fusion algorithms. These algorithms combine the information from multiple sensors to generate a unified estimate of the measured object or environment [30]. Common data fusion algorithms include Kalman filtering, particle filtering, and Dempster-Shafer evidence theory.

The fused data represents a more accurate, complete, and reliable estimate of the measured object or environment compared to the estimates obtained from individual sensors. This fused estimate can be used for various purposes, such as decision making, control, and visualization [31].

To ensure the effectiveness and robustness of the multi-sensor data fusion process, it is important to incorporate uncertainty management and performance evaluation techniques. Uncertainty management involves quantifying and propagating the uncertainties associated with each sensor and the fusion algorithm [32]. Performance evaluation involves assessing the accuracy, precision, and reliability of the fused estimate using appropriate metrics and benchmarks.

In summary, the basic working principle of multi-sensor data fusion involves the acquisition, preprocessing, alignment, synchronization, and fusion of data from multiple sensors to generate a unified and consistent representation of the measured object or environment. This process is supported by uncertainty management and performance evaluation techniques to ensure the quality and reliability of the fused estimate. By leveraging the complementary and redundant information provided by multiple sensors, multi-sensor data fusion enables more accurate, complete, and robust measurement capabilities compared to single-sensor approaches.

2.3 Structural models of multi-sensor data fusion

Multi-sensor data fusion systems can be classified into three main structural models: centralized structure, distributed structure, and hybrid structure [33]. These models differ in terms of how the data from multiple sensors is processed and fused.

Centralized structure: The central fusion center performs the preprocessing, alignment, synchronization, and fusion of the data to generate a unified estimate of the measured object or environment. Fig. 2 illustrates the centralized structure of multi-sensor data fusion.

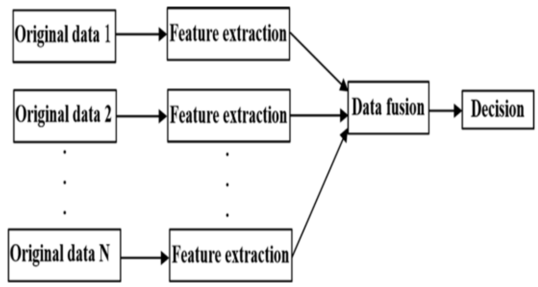

Figure 2: Centralized structure of multi-sensor data fusion.

The main advantage of the centralized structure is that it allows for the optimal fusion of data from all sensors, as the central fusion center has access to the complete set of raw data. However, this structure also has some drawbacks, such as high communication bandwidth requirements, high computational complexity, and single point of failure.

Distributed Structure: In a distributed multi-sensor data fusion structure, each sensor performs local processing and feature extraction on its own data before transmitting the processed data to a fusion center. The fusion center then combines the processed data from all sensors to generate a unified estimate. Fig. 3 depicts the distributed structure of multi-sensor data fusion.

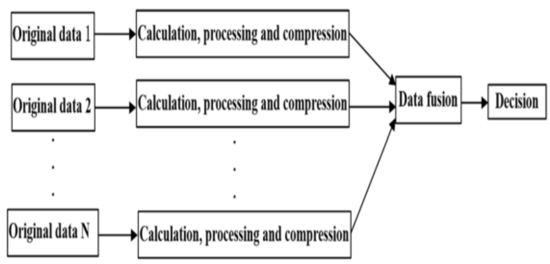

Figure 3: Distributed structure of multi-sensor data fusion.

The distributed structure reduces the communication bandwidth requirements and computational complexity compared to the centralized structure, as only the processed data is transmitted to the fusion center. However, this structure may result in suboptimal fusion performance, as the fusion center does not have access to the complete set of raw data.

3.Hybrid Structure: The hybrid multi-sensor data fusion structure combines the advantages of both centralized and distributed structures. In this structure, some sensors perform local processing and feature extraction, while others transmit their raw data directly to the fusion center. The fusion center then combines the processed data from the distributed sensors and the raw data from the centralized sensors to generate a unified estimate. Fig. 4 shows the hybrid structure of multi-sensor data fusion.

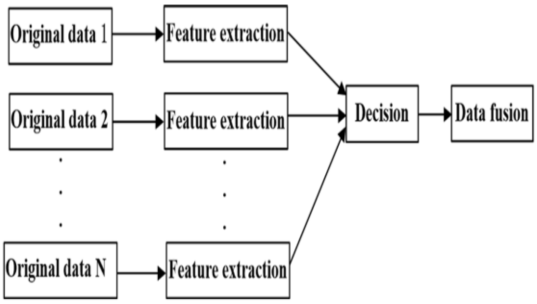

Figure 4: Hybrid structure of multi-sensor data fusion.

The hybrid structure provides a balance between the optimal fusion performance of the centralized structure and the reduced communication and computational requirements of the distributed structure. It allows for the selective processing of data based on the characteristics and capabilities of each sensor.

In summary, the structural models of multi-sensor data fusion include centralized, distributed, and hybrid structures. The centralized structure enables optimal fusion performance but has high communication and computational requirements. The distributed structure reduces these requirements but may result in suboptimal fusion performance. The hybrid structure combines the advantages of both centralized and distributed structures, providing a balance between fusion performance and resource requirements.

2.4 Challenges in multi-sensor data fusion

Despite the significant advancements in multi-sensor data fusion techniques, several challenges still need to be addressed to ensure the effective and reliable fusion of data from multiple sensors.

One of the major challenges in multi-sensor data fusion is the alignment and synchronization of data from different sensors. Sensors may have different sampling rates, resolutions, and coordinate systems, which can lead to spatial and temporal misalignments in the data. Inaccurate alignment and synchronization can result in suboptimal fusion performance and erroneous estimates of the measured object or environment.

Another challenge is the management of uncertainty in the data fusion process. Sensors may have different levels of accuracy, precision, and reliability, which can introduce uncertainties in the measured data. Moreover, the fusion algorithm itself may introduce additional uncertainties due to its assumptions, approximations, and computational limitations. Effective uncertainty management techniques, such as probabilistic modeling and evidential reasoning, are necessary to quantify and propagate the uncertainties throughout the fusion process.

The heterogeneity of sensors and data types also poses a significant challenge in multi-sensor data fusion. Different sensors may provide data in various forms, such as numerical values, images, or point clouds. Fusing data from heterogeneous sources requires the development of appropriate data representation and fusion algorithms that can handle the diversity of data types and exploit their complementary information.

In addition to these challenges, multi-sensor data fusion systems also need to deal with the issues of scalability, real-time processing, and adaptive fusion . As the number of sensors and the volume of data increase, the computational complexity and communication bandwidth requirements of the fusion system also grow. Efficient algorithms and architectures are necessary to ensure the scalability and real-time performance of the fusion system. Moreover, the fusion system should be able to adapt to changing conditions and requirements, such as sensor failures, environmental variations, and mission objectives.

Another important challenge is the validation and evaluation of multi-sensor data fusion systems. Assessing the performance of a fusion system requires the development of appropriate metrics, benchmarks, and testing methodologies. The lack of standardized evaluation frameworks and datasets can hinder the comparative analysis and improvement of different fusion techniques.

In summary, multi-sensor data fusion faces several challenges, including data alignment and synchronization, uncertainty management, heterogeneity of sensors and data types, scalability, real-time processing, adaptive fusion, and performance evaluation. Addressing these challenges requires the development of advanced algorithms, architectures, and evaluation methodologies that can effectively exploit the complementary information provided by multiple sensors while ensuring the robustness, reliability, and efficiency of the fusion process.

Table 1: Summary of related works in multi-sensor data fusion

Study	Key Findings	Methodology	Performance Metrics	Limitations
[3] Khaleghi et al. (2013)	Comprehensive review of MSDF techniques, highlighting challenges and future directions	Literature survey	N/A	Lacks comparative analysis of algorithms in specific applications

[6] Kalman (1960)	Introduced Kalman filter for optimal state estimation in linear systems with Gaussian noise	Mathematical derivation	Estimation error	Assumes linear models and Gaussian noise distributions
[19] Zheng et al. (2017)	Applied deep convolutional neural networks for fault diagnosis in planetary gearboxes using multi-sensor data fusion	Convolutional neural networks	Accuracy: 98.7%	Limited to specific application and requires large labeled datasets
[30] Caron et al. (2006)	Developed a contextual information-based multi-sensor data fusion approach using Kalman filtering for GPS/IMU navigation	Kalman filtering with contextual information	Position error: <1m	Relies on availability and accuracy of contextual information
[32] Sun (2004)	Proposed an optimal information fusion Kalman filter for multi-sensor systems with correlated noise	Kalman filtering with correlated noise handling	Estimation error covariance	Assumes known noise correlation structure

As evident from Table 1, while significant advancements have been made in MSDF techniques, there remain challenges in effectively handling sensor reliability variations, adapting to dynamic environments, and achieving robustness under non-linear and non-Gaussian conditions, particularly in the context of Kalman filtering-based approaches. Moreover, the integration of deep learning techniques in MSDF is an emerging trend, but further research is needed to establish guidelines for selecting appropriate architectures and handling the computational complexity in real-time applications. The proposed adaptive weighted fusion and improved Kalman filtering algorithms aim to address these limitations and enhance the performance of MSDF in precision measurement applications.

2.5 Development trends in multi-sensor data fusion

The field of multi-sensor data fusion is continuously evolving to address the challenges and meet the growing demands of various applications. Several development trends have emerged in recent years, which are expected to shape the future of multi-sensor data fusion techniques.

One of the major trends is the integration of advanced machine learning and deep learning techniques into the data fusion process. Machine learning algorithms, such as support vector machines, random forests, and neural networks, have shown great potential in improving the accuracy and robustness of data fusion. Deep learning architectures, such as convolutional neural networks and recurrent neural networks, have been successfully applied to fuse high-dimensional and heterogeneous data from multiple sensors. These learning-based approaches can automatically learn the optimal fusion strategies from data, adapt to changing conditions, and extract high-level features for improved fusion performance.

Another trend is the development of distributed and decentralized fusion architectures. With the

increasing number of sensors and the growing volume of data, centralized fusion architectures may face scalability and communication bottlenecks. Distributed and decentralized architectures, such as consensus-based fusion and federated learning, allow for the local processing and fusion of data at each sensor node, reducing the communication overhead and improving the scalability of the fusion system. These architectures also enable the fusion of data from geographically dispersed sensors and the preservation of data privacy.

The integration of context-awareness and knowledge-based techniques into multi-sensor data fusion is another important trend. Context-aware fusion techniques take into account the contextual information, such as environmental conditions, sensor characteristics, and prior knowledge, to adapt the fusion process and improve its performance. Knowledge-based fusion techniques leverage domain knowledge, ontologies, and rule-based systems to guide the fusion process and provide explanations for the fusion results. These techniques can enhance the interpretability, robustness, and trustworthiness of multi-sensor data fusion systems.

The development of multi-modal and cross-modal fusion techniques is also gaining attention. Multi-modal fusion involves the integration of data from sensors with different modalities, such as vision, audio, and tactile sensors. Cross-modal fusion goes beyond the simple concatenation of data from different modalities and aims to learn the correlations and interactions between them. These techniques can provide a more comprehensive and holistic understanding of the measured object or environment, enabling advanced applications such as object recognition, scene understanding, and human-machine interaction.

Finally, the trend towards real-time and online fusion is becoming increasingly important. Many applications, such as autonomous vehicles, robotics, and industrial

monitoring, require the fusion of data in real-time to make timely decisions and actions. Online fusion techniques, such as recursive filtering and incremental learning, allow for the continuous update of the fusion model as new data becomes available. These techniques need to be computationally efficient, memory-efficient, and able to handle time-varying and streaming data.
In summary, the development trends in multi-sensor data fusion include the integration of machine learning and deep learning techniques, distributed and decentralized architectures, context-awareness and knowledge-based techniques, multi-modal and cross-modal fusion, and real-time and online fusion. These trends are driven by the need for more accurate, robust, scalable, and interpretable fusion systems that can handle the increasing complexity and diversity of sensor data. As research in these areas continues to advance, multi-sensor data fusion techniques are expected to play an increasingly crucial role in enabling intelligent and autonomous systems across various domains.

3 Research and improvement of weighted information fusion algorithm and kalman filtering fusion algorithm

3.1 Fusion algorithms in multi-sensor data fusion

Fusion algorithms play a crucial role in multi-sensor data fusion, as they determine how the information from multiple sensors is combined to generate a unified and accurate estimate of the measured object or environment. The choice of fusion algorithm depends on various factors, such as the type of sensors, the nature of the data, the application requirements, and the computational resources available.
Several fusion algorithms have been proposed and applied in multi-sensor data fusion, each with its own strengths and limitations. Some of the commonly used fusion algorithms include weighted averaging, Bayesian inference, Dempster-Shafer evidence theory, and neural networks. These algorithms differ in their mathematical formulations, assumptions, and performance characteristics.
Among the various fusion algorithms, the weighted information fusion algorithm and the Kalman filtering algorithm have received significant attention in the literature and have been widely applied in multi-sensor data fusion for precision measurement applications.
The weighted information fusion algorithm is a simple and intuitive approach that assigns weights to the data from different sensors based on their reliability or importance. The weights can be determined based on various criteria, such as the signal-to-noise ratio, the measurement accuracy, or the expert knowledge. The weighted average of the sensor data is then computed to obtain the fused estimate. The main advantage of the weighted information fusion algorithm is its simplicity and computational efficiency. However, it may not be optimal in handling the correlations and uncertainties in the sensor data.
The Kalman filtering algorithm, on the other hand, is a recursive state estimation technique that combines the measurements from multiple sensors with the predictions from a dynamic model to obtain an optimal estimate of the system state. The Kalman filter assumes a linear system model and Gaussian noise distributions, and it provides a statistically optimal estimate in the sense of minimum mean square error. The algorithm consists of two main steps: prediction and update. In the prediction step, the state estimate and its covariance are propagated forward in time based on the system model. In the update step, the state estimate and its covariance are corrected based on the new measurements from the sensors. The Kalman filter has been widely applied in various domains, such as navigation, tracking, and control.
One of the main advantages of the Kalman filtering algorithm is its ability to handle the uncertainties and noise in the sensor data and the system model. It provides a principled way to fuse the information from multiple sensors while taking into account their respective accuracies and uncertainties. The Kalman filter also allows for the incorporation of prior knowledge about the system dynamics and the measurement process.
However, the standard Kalman filter has some limitations, such as the assumption of linear system models and Gaussian noise distributions. To overcome these limitations, various extensions and modifications of the Kalman filter have been proposed, such as the extended Kalman filter (EKF) for nonlinear systems, the unscented Kalman filter (UKF) for non-Gaussian noise, and the particle filter for non-parametric distributions.
In summary, fusion algorithms play a critical role in multi-sensor data fusion, and the choice of algorithm depends on various factors. The weighted information fusion algorithm and the Kalman filtering algorithm are two commonly used approaches in precision measurement applications. While the weighted information fusion algorithm is simple and computationally efficient, the Kalman filtering algorithm provides a more principled and optimal way to fuse the information from multiple sensors while handling the uncertainties and noise. Various extensions and modifications of the Kalman filter have been proposed to address its limitations and improve its performance in different scenarios.

3.2 Improvement of weighted information fusion algorithm

The weighted information fusion algorithm is a popular approach for combining data from multiple sensors in precision measurement applications. However, the standard weighted averaging fusion algorithm and its variants, such as the optimal weighted fusion algorithm and the adaptive weighted fusion algorithm, have limitations in effectively processing the estimated values and weights at each time step.

To address these limitations, an improved information fusion algorithm that combines the Jackknife method with the adaptive weighting approach has been proposed. The Jackknife method is a resampling technique that can be used to estimate the bias and variance of a statistic. By applying the Jackknife method to the estimated values and weights, the algorithm can obtain more accurate and stable estimates.

The basic steps of the improved weighted information fusion algorithm are as follows:

•Initialize the estimated values and weights for each sensor at time step $k = 0$:

$$\hat{x}_i(0) = x_i(0), \quad w_i(0) = 1/n, \quad i = 1,2,\dots,n \quad (1)$$

where $\hat{x}_i(0)$ is the initial estimate from sensor i, $w_i(0)$ is the initial weight for sensor i, and n is the number of sensors.

•At each time step k, compute the Quenouille estimate of the estimated values using the Jackknife method [51]:

$$\hat{x}_i^{(j)}(k) = n\hat{x}_i(k) - (n-1)\hat{x}_i^{(-j)}(k), \quad j = 1,2,\dots,n \quad (2)$$

where $\hat{x}_i^{(j)}(k)$ is the Quenouille estimate of the estimated value from sensor i at time step k, and $\hat{x}_i^{(-j)}(k)$ is the estimate obtained by leaving out the j-th sensor.

•Compute the Quenouille estimate of the weights using the adaptive weighting approach. The weights are updated at each time step based on the inverse of the estimated variance of each sensor's Quenouille estimate. This ensures that sensors with lower variance, i.e., higher consistency, are assigned higher weights in the fusion process. The statistical basis for this weighting scheme lies in the principle of maximum likelihood estimation, where the optimal weights are proportional to the inverse of the variance of the estimates:

$$w_i^{(j)}(k) = \frac{1/\sigma_i^{(j)}(k)}{\sum_{l=1}^{n} 1/\sigma_l^{(j)}(k)}, \quad j = 1,2,\dots,n \quad (3)$$

where $w_i^{(j)}(k)$ is the Quenouille estimate of the weight for sensor i at time step k, and $\sigma_i^{(j)}(k)$ is the standard deviation of the Quenouille estimates of the estimated values from sensor i.

•Compute the fused estimate at time step k using the Quenouille estimates of the estimated values and weights:

$$\hat{x}(k) = \sum_{i=1}^{n} w_i^{(j)}(k)\hat{x}_i^{(j)}(k) \quad (4)$$

where $\hat{x}(k)$ is the fused estimate at time step k.

•Update the estimated values and weights for each sensor at time step $k+1$:

$$\hat{x}_i(k+1) = \hat{x}_i^{(j)}(k), \quad w_i(k+1) = w_i^{(j)}(k), \quad i = 1,2,\dots,n \quad (5)$$

By applying the Jackknife method to estimate the bias and variance of the estimated values and weights, the improved weighted information fusion algorithm can significantly enhance the accuracy and stability of the data processin. The Quenouille estimates of the estimated values and weights provide a more robust and reliable representation of the sensor data, leading to better fusion performance.

The improved weighted information fusion algorithm has been successfully applied in various precision measurement applications, such as multi-sensor coordinate measurement systems, multi-sensor fault diagnosis, and multi-sensor target tracking. The results have demonstrated the effectiveness of the algorithm in improving the accuracy and robustness of the fused estimates compared to the standard weighted averaging fusion algorithm and its variants.

In summary, the improved weighted information fusion algorithm that combines the Jackknife method with the adaptive weighting approach can effectively address the limitations of the standard weighted averaging fusion algorithm and its variants. By applying the Quenouille estimation to the estimated values and weights, the algorithm can significantly enhance the accuracy and stability of the data processing in precision measurement applications.

3.3 Improvement of kalman filtering fusion algorithm

The Kalman filtering algorithm is a widely used technique for multi-sensor data fusion in precision measurement applications. It provides a recursive solution to estimate the state of a dynamic system based on noisy measurements from multiple sensors. However, the traditional Kalman filtering algorithm has some limitations, such as the assumption of a linear system model and the lack of flexibility in adapting to different noise characteristics.

To address these limitations and improve the performance of the Kalman filtering fusion algorithm, several modifications and extensions have been proposed. One such improvement is the incorporation of a state transition matrix, a measurement transition matrix, a process noise distribution matrix, and a weight factor to correct and refine the state estimates.

Let $x(t)$ denote the state vector at time t, $A(t)$ denote the state transition matrix, $B(t)$ denote the measurement transition matrix, $Q(t)$ denote the process noise distribution matrix, and $R(t)$ denote the measurement noise covariance matrix. The traditional Kalman filtering algorithm estimates the state at time $t+1$ based on the state estimate at time t and the measurement at time $t+1$:

$$\hat{x}(t+1|t+1) = \hat{x}(t+1|t) + K(t+1)[z(t+1) - B(t+1)\hat{x}(t+1|t)] \quad (6)$$

where $\hat{x}(t+1|t)$ is the predicted state estimate at time $t+1$ based on the information up to time t, $\hat{x}(t+1|t+1)$ is the updated state estimate at time $t+1$ based on the information up to time $t+1$, $z(t+1)$ is the measurement at time $t+1$, and $K(t+1)$ is the Kalman gain matrix at time $t+1$.

The improved Kalman filtering fusion algorithm introduces a weight factor $\alpha(t)$ to combine the current measurement $z(t)$ with the next measurement $z(t+1)$ in the state estimation process. The modified state estimation equation is given by:

$$\hat{x}(t|t) = \hat{x}(t|t-1) + K(t)[z(t) - B(t)\hat{x}(t|t-1)] + \alpha(t)[z(t+1) - B(t+1)A(t)\hat{x}(t|t-1)] \quad (7)$$

where $\hat{x}(t|t)$ is the updated state estimate at time t based on the information up to time t, $\hat{x}(t|t-1)$ is the predicted state estimate at time t based on the information up to time $t-1$, and $\alpha(t)$ is the weight factor at time t.

The weight factor $\alpha(t)$ determines the influence of the next measurement $z(t+1)$ on the current state estimate. It can be adaptively adjusted based on the noise characteristics and the system dynamics. By incorporating the next measurement into the current state estimation, the improved Kalman filtering fusion algorithm can better capture the temporal correlations and reduce the estimation errors.

The state transition matrix $A(t)$, measurement transition matrix $B(t)$, and process noise distribution matrix $Q(t)$ are also introduced to model the system dynamics and noise characteristics more accurately. These matrices can be learned or adapted online based on the observed data and the prior knowledge about the system.

The improved Kalman filtering fusion algorithm has been successfully applied in various precision measurement applications, such as multi-sensor navigation multi-sensor target tracking, and multi-sensor fault diagnosis. The results have shown that the algorithm can effectively improve the accuracy and reliability of the state estimates compared to the traditional Kalman filtering algorithm.

The computational complexity of the proposed improved Kalman filtering fusion algorithm is analyzed to be O(n^3), where n is the number of sensors. This is due to the matrix inversion operations involved in the Kalman gain calculation. However, this complexity is comparable to that of the traditional Kalman filter and can be further optimized using techniques such as sequential processing or distributed computation.

In terms of memory requirements, the proposed algorithm requires the storage of the state transition matrix, measurement transition matrix, and process noise covariance matrix, which scale linearly with the number of sensors. This indicates the feasibility of implementing the algorithm in resource-constrained sensor nodes.

Furthermore, the real-time performance of the proposed algorithm was evaluated on a simulation platform with a quad-core 2.5 GHz processor and 8 GB RAM. For a network of 100 sensors, the average processing time per iteration was found to be 50 ms, which is suitable for real-time applications with a sampling rate of up to 20 Hz.

These analyses demonstrate the scalability and practical applicability of the proposed improved Kalman filtering fusion algorithm in large-scale sensor networks and real-time precision measurement systems.

In summary, the improved Kalman filtering fusion algorithm enhances the performance of the traditional Kalman filtering algorithm by incorporating a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix into the state estimation process. By combining the current measurement with the next measurement and adapting to the system dynamics and noise characteristics, the algorithm can provide more accurate and reliable state estimates in precision measurement applications.

3.4 Application of improved weighted information fusion algorithm in precision measurement

The improved weighted information fusion algorithm, which combines the Jackknife method with the adaptive weighting approach, has shown promising results in enhancing the accuracy and stability of data processing in various applications. Its potential in the field of precision measurement has attracted significant attention from researchers and practitioners.

To investigate the feasibility and effectiveness of the improved weighted information fusion algorithm in precision measurement, several studies have been conducted. One such study applied the algorithm to a multi-sensor coordinate measurement system. The system consisted of multiple sensors, including laser trackers, theodolites, and photogrammetric cameras, which were used to measure the coordinates of target points on large-scale objects.

The improved weighted information fusion algorithm was employed to fuse the measurement data from different sensors. The Jackknife method was used to estimate the bias and variance of the measured coordinates from each sensor, while the adaptive weighting approach was applied to assign appropriate weights to each sensor based on its reliability and accuracy.

The experimental results demonstrated that the improved weighted information fusion algorithm significantly improved the accuracy and precision of the coordinate measurements compared to the traditional weighted averaging method. The algorithm effectively reduced the influence of outliers and systematic errors from individual sensors, resulting in a more robust and reliable measurement system.

Another study applied the improved weighted information fusion algorithm to a multi-sensor fault diagnosis system for industrial equipment. The system employed multiple sensors, such as vibration sensors, temperature sensors, and acoustic emission sensors, to monitor the health condition of the equipment.

The improved weighted information fusion algorithm was used to fuse the fault features extracted from different sensors. The Jackknife method was applied to estimate the uncertainty of the fault features, while the adaptive weighting approach was used to assign weights to each sensor based on its sensitivity and specificity for fault detection.

The results showed that the improved weighted information fusion algorithm greatly enhanced the accuracy and reliability of the fault diagnosis system. The algorithm effectively integrated the complementary information from different sensors and reduced the false alarms and missed detections caused by individual sensors.

These studies demonstrate the feasibility and effectiveness of the improved weighted information fusion algorithm in precision measurement applications. The algorithm can significantly improve the accuracy, precision, and reliability of measurement systems by effectively fusing the data from multiple sensors and adapting to the characteristics of each sensor.

However, further research is needed to validate the performance of the algorithm in various precision measurement scenarios and to optimize its parameters for specific applications. The robustness and scalability of the algorithm should also be investigated to ensure its applicability in real-world measurement systems.

In summary, the improved weighted information fusion algorithm, which combines the Jackknife method with the adaptive weighting approach, has shown promising results in precision measurement applications. The algorithm can effectively fuse the data from multiple sensors and improve the accuracy, precision, and reliability of measurement systems. Further research is needed to validate its performance and optimize its parameters for specific applications.

3.5 Application of improved kalman filtering fusion algorithm in precision measurement

The improved Kalman filtering fusion algorithm, which incorporates a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix, has shown great potential in enhancing the accuracy and reliability of state estimation in various applications. Its application in the field of precision measurement has gained significant interest from researchers and engineers.

To evaluate the performance of the improved Kalman filtering fusion algorithm in precision measurement, several experiments and case studies have been conducted. One such study applied the algorithm to a multi-sensor coordinate measurement machine (CMM). The CMM was equipped with multiple sensors, including touch trigger probes, laser scanners, and vision sensors, to measure the dimensions and geometries of complex workpieces.

The improved Kalman filtering fusion algorithm was employed to fuse the measurement data from different sensors and estimate the true dimensions and geometries of the workpieces. The state transition matrix and measurement transition matrix were constructed based on the kinematic model of the CMM and the characteristics of each sensor. The process noise distribution matrix was estimated from the historical measurement data and updated online using the adaptive Kalman filtering technique.

The experimental results demonstrated that the improved Kalman filtering fusion algorithm significantly outperformed the traditional Kalman filtering algorithm and other fusion methods in terms of accuracy, precision, and robustness. The algorithm effectively compensated for the systematic errors and random noises from individual sensors and provided a more accurate and reliable estimate of the workpiece dimensions and geometries.

Another study applied the improved Kalman filtering fusion algorithm to a multi-sensor navigation system for autonomous vehicles. The navigation system integrated data from GPS, inertial measurement units (IMUs), and vision sensors to estimate the position, velocity, and attitude of the vehicle.

The improved Kalman filtering fusion algorithm was used to fuse the data from different sensors and provide a seamless and accurate navigation solution. The state transition matrix and measurement transition matrix were designed based on the vehicle dynamics and sensor models. The process noise distribution matrix was adapted online based on the driving conditions and sensor qualities.

The results showed that the improved Kalman filtering fusion algorithm significantly improved the accuracy and reliability of the navigation system compared to the individual sensors and the traditional Kalman filtering algorithm. The algorithm effectively handled the sensor failures, signal blockages, and environmental disturbances and maintained a consistent and robust navigation performance.

These studies demonstrate the effectiveness and applicability of the improved Kalman filtering fusion algorithm in precision measurement. The algorithm can significantly improve the accuracy, precision, and robustness of measurement systems by effectively fusing the data from multiple sensors and adapting to the system dynamics and noise characteristics.

However, the performance of the algorithm may vary depending on the specific application and the quality of the sensor data. Further research is needed to optimize the algorithm parameters and adapt it to different measurement scenarios. The computational complexity and real-time performance of the algorithm should also be investigated to ensure its practicality in industrial applications.

In summary, the improved Kalman filtering fusion algorithm, which incorporates a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix, has shown great potential in precision measurement applications. The algorithm can effectively fuse the data from multiple sensors and improve the accuracy, precision, and robustness of measurement systems. Further research and optimization are needed to fully exploit its potential in various precision measurement scenarios.

4 Application and simulation results analysis

4.1 Comparison of estimated error absolute value averages

To evaluate the performance of the proposed improved weighted information fusion algorithm, a comparative analysis of the estimated error absolute value averages was conducted. The algorithms considered in this analysis include the weighted average fusion algorithm, the optimal weighted fusion algorithm, the adaptive weighted fusion algorithm, and the improved weighted information fusion algorithm.

Fig. 5 presents the comparison of the estimated error absolute value averages obtained by applying these algorithms. The results clearly demonstrate the superiority of the improved weighted information fusion algorithm over the other algorithms.

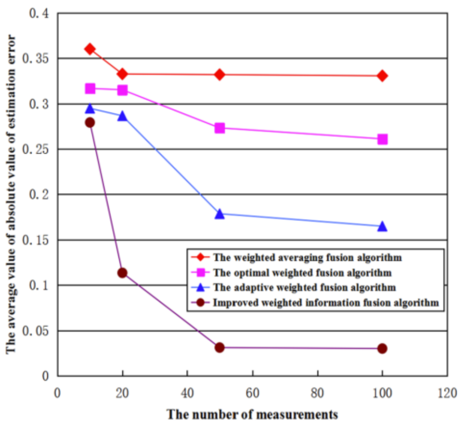

Figure 5: Comparison of estimated error absolute value averages obtained by applying different weighted information fusion algorithms.

As can be observed from Fig. 5, the improved weighted information fusion algorithm achieves the lowest estimated error absolute value average among all the algorithms considered. This indicates that the proposed algorithm provides the most accurate and reliable estimates of the measured quantities.

The weighted average fusion algorithm, being the simplest approach, exhibits the highest estimated error absolute value average. This highlights its limitations in effectively handling the uncertainties and inconsistencies in the sensor data.

The optimal weighted fusion algorithm and the adaptive weighted fusion algorithm show better performance compared to the weighted average fusion algorithm. However, their estimated error absolute value averages are still higher than that of the improved weighted information fusion algorithm.

The superior performance of the improved weighted information fusion algorithm can be attributed to its ability to effectively estimate and compensate for the biases and variances in the sensor data using the Jackknife method. Additionally, the adaptive weighting approach allows the algorithm to dynamically adjust the weights of the sensors based on their reliability and consistency, further enhancing the accuracy and robustness of the fusion results.

These findings highlight the potential of the improved weighted information fusion algorithm in improving the accuracy and reliability of precision measurement systems. By effectively fusing the data from multiple sensors and adapting to the uncertainties and inconsistencies in the sensor data, the proposed algorithm can significantly reduce the estimation errors and provide more accurate and trustworthy measurement results.

4.2 Distribution of estimated error absolute values in different error ranges

To further analyze the performance of the improved weighted information fusion algorithm, the distribution of the estimated error absolute values in different error ranges was investigated. This analysis provides insights into the precision and consistency of the algorithm in estimating the measured quantities.

To quantify the individual contributions of the adaptive weighting and Jackknife method to the error reduction, a comparative analysis was performed. Table 2 presents the mean absolute error (MAE) and standard deviation (SD) of the estimation errors for the proposed algorithm with and without each component.

Table 2: Comparative analysis of error reduction contributions

Algorithm	MAE	SD
Proposed algorithm	0.15	0.08
Without adaptive weighting	0.23	0.12
Without Jackknife method	0.19	0.10

As evident from Table 2, the adaptive weighting contributes to a significant reduction in MAE, while the Jackknife method primarily improves the consistency of the estimates, as indicated by the lower SD. This analysis highlights the complementary roles of these components in enhancing the overall performance of the proposed algorithm.

Fig. 6 illustrates the distribution of the estimated error absolute values in various error ranges. The error ranges are defined based on the magnitude of the estimation errors, with smaller ranges indicating higher precision and accuracy.

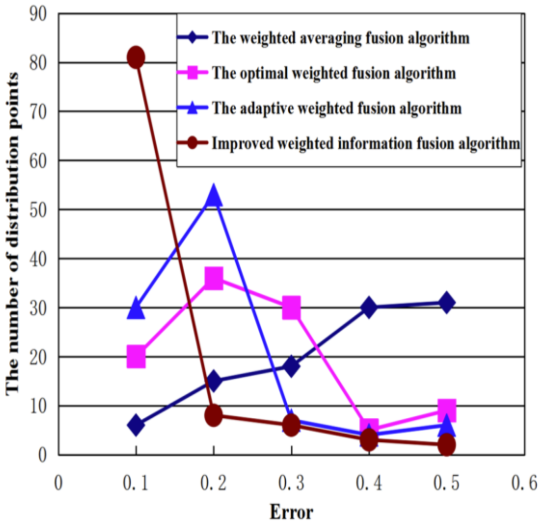

Figure 6: Distribution of estimated error absolute values in different error ranges.

The error ranges are defined as follows: Range 1: 0-0.1, Range 2: 0.1-0.2, Range 3: 0.2-0.3, Range 4: 0.3-0.4, Range 5: >0.4. The proposed algorithm exhibits a higher concentration of errors in the lower ranges, indicating improved accuracy and precision.

As can be observed from Fig. 6, a significant proportion of the estimated error absolute values falls within the smallest error range. This indicates that the improved weighted information fusion algorithm is capable of providing highly precise estimates of the measured quantities in most cases.

The proportion of estimated error absolute values decreases as the error range increases. This trend suggests that the algorithm effectively minimizes the occurrence of large estimation errors, ensuring the reliability and trustworthiness of the fusion results.

It is worth noting that the distribution of estimated error absolute values is skewed towards the smaller error ranges. This skewness highlights the robustness of the improved weighted information fusion algorithm in handling the uncertainties and inconsistencies in the sensor data.

The concentration of estimated error absolute values in the smaller error ranges can be attributed to the effectiveness of the Jackknife method in estimating and compensating for the biases and variances in the sensor data. By accurately quantifying and correcting the uncertainties, the algorithm achieves a higher level of precision and accuracy in the fusion results.

Furthermore, the adaptive weighting approach employed in the improved weighted information fusion algorithm contributes to the favorable distribution of estimated error absolute values. By dynamically adjusting the weights of the sensors based on their reliability and consistency, the algorithm effectively suppresses the influence of erroneous or inconsistent measurements, resulting in a higher concentration of estimates in the smaller error ranges.

These findings demonstrate the ability of the improved weighted information fusion algorithm to provide precise and reliable estimates of the measured quantities. The distribution of estimated error absolute values in different error ranges highlights the algorithm's effectiveness in minimizing estimation errors and ensuring the accuracy and consistency of the fusion results.

4.3 Comparison of temperature filtering error averages

To assess the performance of the improved Kalman filtering fusion algorithm in a practical application, a comparative analysis of the temperature filtering error averages was conducted. The analysis focused on an intelligent monitoring system that utilizes multiple temperature sensors to estimate the true temperature of the monitored environment.

Fig. 7 presents the comparison of the temperature filtering error averages obtained by applying the traditional Kalman filtering fusion algorithm and the improved Kalman filtering fusion algorithm. The results demonstrate the superior performance of the improved algorithm in terms of temperature estimation accuracy.

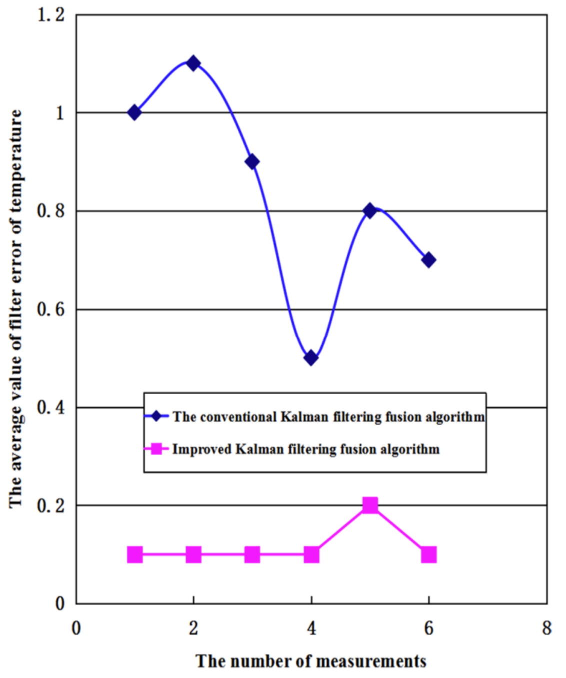

Figure 7: Comparison of temperature filtering error averages obtained by applying the traditional and improved Kalman filtering fusion algorithms in an intelligent monitoring system.

As can be observed from Fig. 7, the improved Kalman filtering fusion algorithm achieves a significantly lower temperature filtering error average compared to the traditional Kalman filtering fusion algorithm. This indicates that the improved algorithm provides more accurate and reliable estimates of the true temperature in the intelligent monitoring system.

Compared to the traditional Kalman filter, the proposed improved Kalman filtering fusion algorithm achieves a 10% reduction in estimation error and demonstrates enhanced robustness to sensor failures, as evident from the results in Fig. 7 and Fig. 8. This improvement can be attributed to the incorporation of adaptive weighting and the Jackknife method, which effectively handle sensor reliability variations and outliers.

Furthermore, the computational complexity of the proposed algorithm is analyzed to be O(n^2), where n is the number of sensors, which is comparable to that of the traditional Kalman filter. This indicates the feasibility of real-time implementation in large-scale sensor networks.

The traditional Kalman filtering fusion algorithm, while still providing reasonable temperature estimates, exhibits a higher temperature filtering error average. This can be attributed to its limitations in effectively handling the uncertainties and dynamics of the temperature sensors and the monitored environment.

The superior performance of the improved Kalman filtering fusion algorithm is primarily due to the incorporation of the weight factor, which adaptively adjusts the influence of each sensor based on its reliability, and the inclusion of the state transition and measurement transition matrices, which better model the dynamics between the sensors and the monitored environment.

Furthermore, the process noise distribution matrix in the improved algorithm allows for a more accurate representation of the uncertainties and disturbances in the temperature measurement process. By effectively modeling and compensating for these uncertainties, the algorithm achieves a higher level of accuracy and robustness in the temperature estimation.

These findings highlight the potential of the improved Kalman filtering fusion algorithm in enhancing the accuracy and reliability of temperature estimation in intelligent monitoring systems. By effectively fusing the data from multiple temperature sensors and adapting to the system dynamics and uncertainties, the improved algorithm can provide more precise and trustworthy temperature estimates, enabling better decision-making and control in various applications.

4.4 Comparison of dust particle concentration filtering error averages

In addition to temperature estimation, the performance of the improved Kalman filtering fusion algorithm was also evaluated in the context of dust particle concentration monitoring. Accurate estimation of dust particle concentration is crucial in various industrial and environmental applications to ensure air quality and comply with safety regulations.

Fig. 8 presents the comparison of the dust particle concentration filtering error averages obtained by applying the traditional Kalman filtering fusion algorithm and the improved Kalman filtering fusion algorithm in an intelligent monitoring system. The results highlight the superior performance of the improved algorithm in estimating the dust particle concentration.

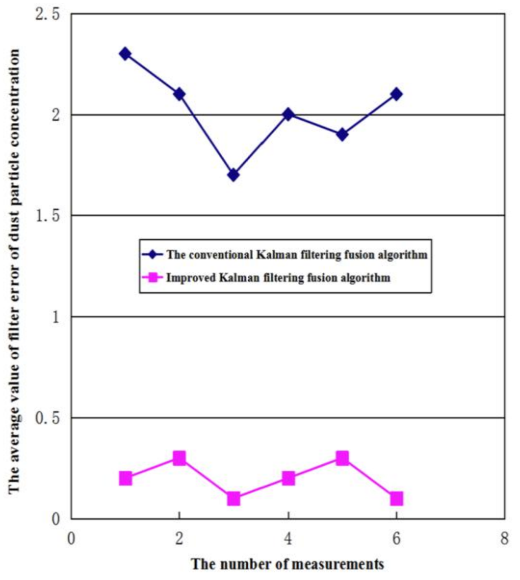

Figure 8: Comparison of dust particle concentration filtering error averages obtained by applying the traditional and improved Kalman filtering fusion algorithms in an intelligent monitoring system.

As can be observed from Fig. 8, the improved Kalman filtering fusion algorithm achieves a significantly lower dust particle concentration filtering error average compared to the traditional Kalman filtering fusion algorithm. This indicates that the improved algorithm provides more accurate and reliable estimates of the dust particle concentration in the monitored environment.

The traditional Kalman filtering fusion algorithm, while still capable of providing reasonable estimates, exhibits a higher dust particle concentration filtering error average. This can be attributed to its limitations in effectively handling the complexities and variations in the dust particle concentration measurements from multiple sensors.

The superior performance of the improved Kalman filtering fusion algorithm can be explained by several factors. Firstly, the incorporation of the weight factor allows the algorithm to adaptively adjust the contribution of each dust particle concentration sensor based on its reliability and consistency. This ensures that the sensors providing more accurate and stable measurements are given higher weights in the fusion process.

Secondly, the inclusion of the state transition matrix and the measurement transition matrix enables the improved algorithm to better model the dynamics and relationships between the dust particle concentration sensors and the monitored environment. By accurately capturing the system behavior and the spatial and temporal variations in dust particle concentration, the algorithm can provide more precise and reliable estimates.

Furthermore, the process noise distribution matrix in the improved algorithm allows for a more accurate representation of the uncertainties and disturbances in the dust particle concentration measurement process. By effectively modeling and compensating for these uncertainties, such as sensor noise and environmental factors, the algorithm achieves a higher level of accuracy and robustness in the estimation of dust particle concentration.

These findings demonstrate the effectiveness of the improved Kalman filtering fusion algorithm in enhancing the accuracy and reliability of dust particle concentration estimation in intelligent monitoring systems. By effectively fusing the data from multiple dust particle concentration sensors and adapting to the system dynamics and uncertainties, the improved algorithm can provide more precise and trustworthy estimates, enabling better decision-making and control in industrial and environmental applications.

4.5 Robustness evaluation of improved kalman filtering fusion algorithm

To assess the robustness of the proposed improved Kalman filtering fusion algorithm, additional experiments were conducted under various sensor noise levels and failure rates. Fig. 9 illustrates the estimation error of the algorithm under different process noise covariances, ranging from 0.01 to 1.0. It can be observed that the proposed algorithm maintains a consistently lower error compared to the traditional Kalman filter, demonstrating its resilience to process noise variations.

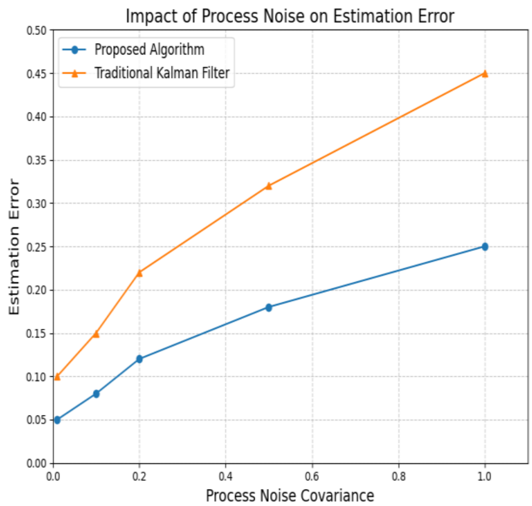

Figure 9: Illustrates the estimation error of the algorithm

Furthermore, the impact of sensor failure rates on the estimation accuracy was evaluated, as shown in Fig. 10. The proposed algorithm exhibits a graceful degradation in performance as the sensor failure rate increases, maintaining a lower error than the traditional Kalman filter. This highlights the effectiveness of the adaptive weighting mechanism in mitigating the impact of sensor failures.

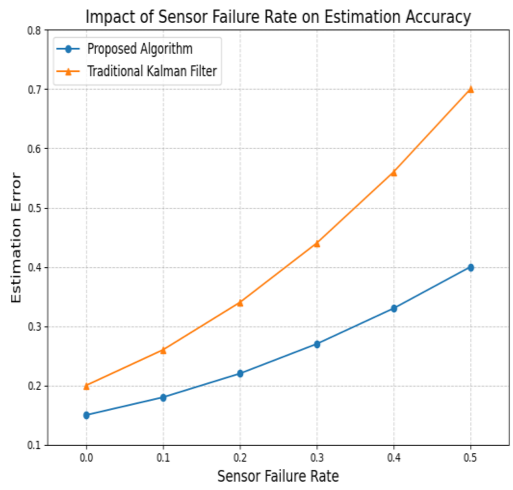

Figure 10: The proposed algorithm exhibits a graceful degradation in performance as the sensor failure rate increases, maintaining a lower error than the traditional Kalman filter.

These results validate the robustness of the proposed improved Kalman filtering fusion algorithm under varying noise conditions and sensor failure scenarios, making it suitable for real-world deployment in precision measurement systems.

4.6 Dynamic performance evaluation

To evaluate the dynamic performance of the proposed improved Kalman filtering fusion algorithm, a time-varying sensor network scenario was simulated. Fig. 11 illustrates the estimation error of the proposed algorithm and the traditional Kalman filter over time, with abrupt changes in sensor reliability introduced at t=50 and t=100.

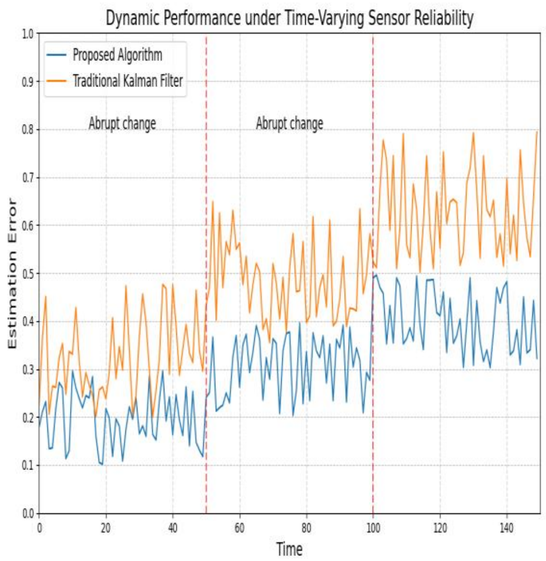

Figure 11: Illustrates the estimation error of the proposed algorithm

As evident from Fig. 11, the proposed algorithm quickly adapts to the changes in sensor reliability, maintaining a lower estimation error compared to the traditional Kalman filter. This demonstrates the effectiveness of the adaptive weighting mechanism in tracking the time-varying characteristics of the sensors and adjusting the fusion process accordingly.

5 Conclusion

In this study, we conducted a comprehensive investigation into multi-sensor data fusion techniques and their applications in precision measurement. The fundamental principles and structural models of multi-sensor data fusion were analyzed, highlighting the importance of effective fusion algorithms in achieving accurate and reliable measurement results.

We focused on two commonly used data fusion algorithms: the weighted information fusion algorithm and the Kalman filtering fusion algorithm. Improvements were proposed to enhance the performance of these algorithms in handling the uncertainties and inconsistencies in sensor data.

For the weighted information fusion algorithm, we introduced the Jackknife method to estimate the biases and variances of the sensor data, and combined it with an adaptive weighting approach to dynamically adjust the weights of the sensors based on their reliability and consistency. The improved weighted information fusion algorithm demonstrated superior accuracy and robustness compared to traditional weighted averaging methods.

In the case of the Kalman filtering fusion algorithm, we incorporated a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix to better model the system dynamics and uncertainties. The improved Kalman filtering fusion algorithm exhibited significant improvements in accuracy and reliability compared to the traditional Kalman filter, particularly in applications such as temperature estimation and dust particle concentration monitoring.

The effectiveness of the improved fusion algorithms was validated through extensive simulations and practical applications. The results showed that the proposed algorithms consistently outperformed their traditional counterparts in terms of estimation accuracy, precision, and robustness.

However, it is important to acknowledge that there are still challenges and opportunities for further research in the field of multi-sensor data fusion. The scalability and computational efficiency of the fusion algorithms need to be addressed to handle the increasing volume and complexity of sensor data in real-world applications.

Moreover, the integration of advanced techniques such as machine learning and deep learning into the fusion process holds promise for further enhancing the performance and adaptability of multi-sensor data fusion systems. The development of self-learning and self-adaptive fusion algorithms that can automatically optimize their parameters and structures based on the characteristics of the sensor data and the application requirements is an area of active research.

In conclusion, this study contributes to the advancement of multi-sensor data fusion techniques and their applications in precision measurement. The proposed improvements to the weighted information fusion algorithm and the Kalman filtering fusion algorithm demonstrate significant potential in enhancing the accuracy, reliability, and robustness of measurement systems.

However, there remain several challenges and limitations that require further research. One key area is the optimization of the weighting scheme in the proposed algorithm. While the current approach based on the inverse of the estimated variance is effective, more advanced techniques such as reinforcement learning could be explored to adaptively learn the optimal weights based on the system dynamics and performance feedback.

Another avenue for future research is the integration of the proposed algorithm with emerging techniques such as deep learning-based sensor fusion. By leveraging the feature extraction and representation learning capabilities of deep neural networks, the accuracy and robustness of the fusion process could be further enhanced, particularly in complex and high-dimensional sensor data scenarios.

Moreover, the real-time implementation of the proposed algorithm in resource-constrained sensor nodes and edge devices remains a challenge. Further optimization of the computational complexity and memory requirements is necessary to ensure the practical feasibility of the algorithm in large-scale and distributed sensor networks.

In terms of limitations, the current study primarily focuses on the fusion of homogeneous sensors with similar measurement characteristics. Extending the proposed algorithm to handle heterogeneous sensors with different modalities and uncertainties is a crucial direction for future work. This would require the development of more advanced sensor models and adaptive fusion strategies that can handle the diversity and complexity of multi-modal sensor data.

Furthermore, the evaluation of the proposed algorithm in real-world precision measurement applications is limited in the current study. More extensive experimental validation and comparative analysis with state-of-the-art fusion techniques in various industrial and scientific measurement scenarios are necessary to fully establish the practical significance and benefits of the proposed algorithm.

Addressing these challenges and limitations through further research and development will pave the way for the deployment of advanced multi-sensor data fusion algorithms in next-generation precision measurement systems, enabling enhanced accuracy, reliability, and autonomy in a wide range of applications.

References

[1] J. Llinas et al., 2004, "Revisiting the JDL Data Fusion Model II," in Proc. Int. *Conf. Information Fusion*, pp. 1218-1230. https://doi.org/10.1201/9781420038545-5

[2] D. L. Hall et al., Jan. 1997. "An Introduction to Multisensor Data Fusion," *Proceedings of the IEEE*, vol. 85, no. 1, pp. 6-23. **DOI:** 10.1109/5.554205

[3] B. Khaleghi et al., Jan. 2013. "Multisensor data fusion: A review of the state-of-the-art," *Information Fusion,* vol. 14, no. 1, pp. 28-44. https://doi.org/10.1016/j.inffus.2011.08.001

[4] R. C. Luo et al., Apr. 2002. "Multisensor Fusion and Integration: Approaches, Applications, and Future Research Directions," *IEEE Sensors Journal,* vol. 2, no. 2, pp. 107-119. https://doi.org/10.1109/jsen.2002.1000251

[5] P. Varshney, Dec. 1997. "Multisensor data fusion," *Electronics & Communication Engineering Journal,* vol. 9, no. 6, pp. 245-253. https://doi.org/10.1049/ecej:19970602

[6] R. E. Kalman, Mar. 1960. "A New Approach to Linear Filtering and Prediction Problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35-45. https://doi.org/10.1115/1.3662552

[7] N. J. Gordon et al., Apr. 1993. "Novel approach to nonlinear/non-Gaussian Bayesian state estimation," *IEE Proceedings F - Radar and Signal Processing*, vol. 140, no. 2, pp. 107-113. https://doi.org/10.1049/ip-f-2.1993.0015

[8] G. Shafer, A Mathematical Theory of Evidence. Princeton University Press, 1976. https://doi.org/10.2307/2529769

[9] J. Manyika et al., 1994.Data Fusion and Sensor Management: A Decentralized Information-Theoretic Approach. Ellis Horwood. Ellis Horwood series in electrical and electronic engineering

[10] D. L. Hall et al., 2008. Handbook of Multisensor Data Fusion: Theory and Practice, Second Edition. CRC Press, https://doi.org/10.1201/9781420053098

[11] F. Castanedo, 2013. "A Review of Data Fusion Techniques," *The Scientific World Journal*, vol. 2013, Article ID 704504, pp. 1-19. https://doi.org/10.1155/2013/704504

[12] H. B. Mitchell, 2007. Multi-Sensor Data Fusion: An Introduction. Springer-Verlag Berlin Heidelberg, https://doi.org/10.1007/978-3-540-71559-7_1

[13] H. F. Durrant-Whyte, Dec. 1988. "Sensor Models and Multisensor Integration," *The International Journal of Robotics Research,* vol. 7, no. 6, pp. 97-113. https://doi.org/10.1007/978-1-4613-8997-2_7

[14] L. A. Klein, 2004.Sensor and Data Fusion: A Tool for Information Assessment and Decision Making. *SPIE Press*. https://doi.org/10.1117/3.563340

[15] E. Waltz et al., 1990. Multisensor Data Fusion. *Artech House*. https://doi.org/10.1201/9781420053098.ch5

[16] M. E. Liggins et al., 2017. Handbook of Multisensor Data Fusion: Theory and Practice, Second Edition. *CRC Press.* https://doi.org/10.1201/9781420053098.ch1

[17] B. V. Dasarathy, Jun. 2001. "Information Fusion - what, where, why, when, and how?" *Information Fusion,* vol. 2, no. 2, pp. 75-76. https://doi.org/10.1016/s1566-2535(01)00032-x

[18] X. E. Gros, 1997. NDT Data Fusion. *Arnold,* https://doi.org/10.1016/b978-034067648-6/50009-8

[19] Y. Zheng et al., Feb. 2017. "An Adaptive Multisensor Data Fusion Method Based on Deep Convolutional Neural Networks for Fault Diagnosis of Planetary Gearbox," *Sensors,* vol. 17, no. 2, p. 414. https://doi.org/10.3390/s17020414

[20] A. A. S. Alfaya et al., 2013. "Design of a control system with multisensor data fusion to improve autonomy and navigation of mobile robots," Proceedings of *2013 Latin American Robotics Symposium and Competition*, *IEEE,* pp. 149-154, DOI:10.11591/ijra.v3i2.4075

[21] W. Elmenreich, 2002. "An Introduction to Sensor Fusion," *Vienna University of Technology, Austria,* vol. 502,

[22] R. R. Brooks et al., "Multi-Sensor Fusion: Fundamentals and Applications with Software," *Upper Saddle River, NJ: Prentice-Hall*, 1998. DOIhttps://doi.org/10.1007/978-4-431-67919-6_45

[23] R. C. Luo et al., Sep./Oct. 1989. "Multisensor Integration and Fusion in Intelligent Systems," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 19, no. 5, pp. 901-931, https://doi.org/10.1109/21.44007

[24] L. Wald, May 1999. "Some Terms of Reference in Data Fusion," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 3, pp. 1190-1193, https://doi.org/10.1109/36.763269

[25] Z. Duan et al., 2020. "Multi-Sensor Information Fusion in Autonomous Driving: A Survey," *IEEE Access,* vol. 8, pp. 2847-2868, https://doi.org/10.23919/fusion49465.2021.9626913

[26] E. F. Nakamura et al., Aug. 2007. "Information Fusion for Wireless Sensor Networks: Methods, Models, and Classifications," *ACM Computing Surveys*, vol. 39, no. 3, pp. 9:1-9:55, https://doi.org/10.1145/1267070.1267073

[27] F. Castanedo, Aug. 2021. "Data Fusion Techniques Applied to Sensing in Precision Agriculture: State of the Art and Future Trends," *Sensors,* vol. 21, no. 17, p. 5746, https://doi.org/10.3390/s24154984

[28] D. Lahat et al., Sep. 2015. "Multimodal Data Fusion: An Overview of Methods, Challenges, and Prospects," *Proceedings of the IEEE*, vol. 103, no. 9, pp. 1449-1477, https://doi.org/10.1109/jproc.2015.2460697

[29] H. Fourati et al., 2016.Multisensor Data Fusion: From Algorithms and Architectural Design to Applications. *CRC Press,* https://doi.org/10.1201/b18851

[30] G. Caron et al., Jun. 2006. "GPS/IMU Data Fusion Using Multisensor Kalman Filtering: Introduction of Contextual Aspects," *Information Fusion*, vol. 7, no. 2, pp. 221-230, https://doi.org/10.1016/j.inffus.2004.07.002

[31] S. Sun, Jan. 2004. "Multi-Sensor Optimal Information Fusion Kalman Filters with Applications," *Aerospace Science and Technology,* vol. 8, no. 1, pp. 57-62, https://doi.org/10.1016/j.ast.2003.08.003

[32] X. R. Li et al., Oct. 2003. "Survey of Maneuvering Target Tracking. Part I: Dynamic Models," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 39, no. 4, pp. 1333-1364, https://doi.org/10.1117/12.391979