A Review of Statistical Modeling and Inference Methods for UAV Airborne Sensors: From State Estimation to Probabilistic Uncertainty Perception

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Abstract: The autonomous flight capability of Unmanned Aerial Vehicles (UAVs) in complex dynamic environments highly depends on the accurate perception of the environment and their own state by onboard sensors. However, limited by sensor noise, model mismatch, observation heterogeneity, and external environmental disturbances, the output of onboard sensors inherently possesses significant uncertainty and randomness. How to transform imperfect, multi-source, and asynchronous sensor observations into reliable state estimation and environmental cognition results through statistical modeling and inference methods has become one of the core issues in UAV perception system research. This paper systematically reviews the development of research related to UAV onboard sensors from a statistical perspective, focusing on the application and evolution of statistical modeling, state estimation, and multi-sensor fusion methods in UAV perception systems. First, it summarizes the typical statistical observation models and noise characteristics of inertial sensors, satellite navigation, vision, lidar, and novel neuromorphic sensors, and analyzes key statistical issues such as random walk, non-Gaussian noise, and time-dependent errors. Subsequently, based on the Bayesian state estimation framework, this paper systematically reviews the application progress of Kalman filtering, error state filtering, particle filtering, and robust statistical methods in UAV navigation and localization, and compares and analyzes the statistical nature of loosely coupled and tightly coupled multi-sensor fusion strategies. Building upon this, it further discusses joint probabilistic modeling methods for heterogeneous sensors such as vision, inertial, and radar, as well as the fusion trend of statistical learning and deep models in high-dimensional perception tasks. Finally, this paper summarizes the role and limitations of statistical methods in UAV airborne sensor research and looks forward to future development directions oriented towards uncertainty perception (the capability to explicitly quantify the reliability of perception results), risk-constrained decision-making (strategies that incorporate estimation variance into control loops to ensure operational safety), and integrated sensing-computing architectures.

Keywords: UAV, airborne sensor, statistical modeling, state estimation, multi-sensor fusion, uncertainty perception.

1. INTRODUCTION

1.1. Research Background and Problem Definition

The widespread application of unmanned aerial vehicles (UAVs) in environmental monitoring, urban inspection, disaster response, and autonomous transportation is driving their transition from remote-controlled flight to fully autonomous intelligent operation. This trend places increasingly higher demands on autonomous perception. Furthermore, efficient statistical algorithms directly contribute to sustainable flight technologies by reducing computational power consumption, thereby extending battery life and mission duration for green UAV operations [1, 2]. However, due to the strict size, weight, and power consumption (SWaP) constraints of micro-UAVs, onboard sensors often employ low-cost microelectromechanical systems (MEMS) devices or consumer-grade optical lenses. Compared with high-precision professional surveying equipment or large aircraft avionics systems, these lightweight sensors have inherent deficiencies in measurement accuracy, stability, and anti-interference capabilities, resulting in significant systematic errors and random noise in the raw observation data.

Furthermore, the working conditions faced by UAVs during flight are far more severe than those faced by ground robots or fixed monitoring stations. This stringency is not only reflected in the motion ambiguity and strong vibration interference caused by high dynamic maneuvering, but also in the unpredictability of the external unstructured environment [3, 4]. For example, multipath effects in urban canyons can severely distort GNSS signals, weak textures or drastic changes in lighting indoors can lead to failure of visual feature tracking, and airflow disturbances during flight can introduce nonlinear dynamic noise [5, 6]. The coupling effect of these internal and external factors makes airborne sensor data inevitably exhibit significant uncertainty, time-varying and random characteristics. In essence, airborne sensors do not directly provide precise physical quantities, but rather random observations of the real state. Sensor noise, system bias, time drift, multipath effects and environmental disturbances make UAV perception

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E-ISSN: 3083-3450/2025

problems inherently statistical [7, 8]. For example, zero bias drift in the inertial measurement unit can be modeled as a random walk process [9], outliers and non-Gaussian noise are common in visual and lidar observations [10], and time asynchrony and spatial calibration errors between multi-sensor systems further exacerbate the uncertainty of state estimation [11]. Therefore, the core issue in the research of UAV airborne sensors has gradually evolved from simply improving hardware accuracy to: how to recover reliable state and environmental information from imperfect sensor observations through statistical modeling and inference methods [12, 13].

1.2. The Core Role of Statistical Methods

Statistical methods provide a systematic modeling and inference framework for UAV perception systems, enabling uncertainty to be explicitly described, propagated, and utilized [14, 15]. In navigation and positioning tasks, Kalman filtering and its extended forms, by introducing probabilistic models, achieve optimal fusion of inertial, satellite navigation, and auxiliary sensor data [16, 17]. In visual and lidar perception, statistical methods based on least squares and robust estimation have become the theoretical basis for the problem of simultaneous localization and mapping (SLAM) [18, 19]. In multi-sensor systems in complex environments, Bayesian inference provides a unified perspective for joint modeling of heterogeneous observations. As the application scenarios of UAVs continue to expand, traditional statistical methods based on Gaussian assumptions and linear approximations have gradually revealed their limitations. On the one hand, actual sensor noise often exhibits non-Gaussian, heavy-tailed, or time-dependent characteristics, leading to a decline in the performance of classical filtering methods in complex environments [20]. On the other hand, the high-dimensional data generated by multimodal perception systems causes the state space to expand rapidly, increasing the complexity of modeling and inference [21]. To address these challenges, robust statistical methods, particle filtering, stochastic optimization, and statistical learning methods have been gradually introduced into UAV perception research, driving the transformation of UAVs from "deterministic control" to "uncertainty perception and decision-making."

The success of deep learning in UAV visual perception in recent years has not diminished the importance of statistical methods. On the contrary, increasing research shows that deep models can essentially be regarded as approximators of complex probability distributions, and their reliable application in UAV systems still relies on uncertainty modeling, confidence assessment, and statistical inference mechanisms [22-24]. Therefore, re-examining UAV airborne sensor research from a statistical perspective is of great significance for understanding the applicability boundaries of existing methods and guiding future system design.

1.3. Existing Limitations and Contributions of This Paper

Currently, most review studies on UAV airborne sensors focus on specific sensor types or single technical directions, such as inertial navigation systems, visual SLAM, or lidar perception. Unlike traditional reviews that predominantly focus on hardware specifications or isolated algorithmic implementations (e.g., specific Visual SLAM pipelines), this paper distinguishes itself by establishing a unified statistical framework. We systematically deconstruct UAV perception into stochastic observation, probabilistic inference, and uncertainty quantification, revealing the intrinsic mathematical connections between seemingly distinct technologies. Furthermore, some reviews focus more on engineering implementation and pay insufficient attention to the sources of uncertainty and their propagation mechanisms within the system, limiting their guiding significance for UAV perception problems in complex environments.

To address these shortcomings, this paper provides a systematic review of UAV airborne sensor research from a statistical perspective, aiming to construct a unified framework for understanding. The main contributions of this paper include:

(1) Summarizing the statistical characteristics and error models of common airborne sensors from the perspective of stochastic observation modeling;

(2) Systematically reviewing commonly used statistical inference methods and their evolution in UAV navigation, localization, and mapping within the Bayesian state estimation framework;

(3) Analyzing the statistical nature of multi-sensor fusion strategies and discussing the role of statistical learning methods in high-dimensional perception tasks;

(4) Prospecting future research directions for uncertainty perception and risk-constrained decision-making.

Through this review, this paper hopes to provide a systematic perspective centered on statistical modeling and inference for UAV airborne sensor research, offering reference for researchers in related fields in terms of method selection and system design.

1.4. Review Scope and Methodology

To ensure a comprehensive review, we utilized databases such as IEEE Xplore, ScienceDirect, and Web of Science. The search keywords included "UAV state estimation," "sensor fusion," "statistical inference," and "uncertainty quantification." We prioritized literature from the last decade (2015–2025) to capture recent advancements in probabilistic perception and deep learning integration, while also retaining foundational classical theories.

2. STATISTICAL OBSERVATION MODELING OF AIRBORNE SENSORS

2.1. Unified Statistical Observation Framework

In UAV perception systems, different types of airborne sensors (such as inertial, satellite navigation, vision, and lidar) differ significantly in their physical mechanisms and output formats. However, from a statistical perspective, their observation process can be uniformly described as random sampling of the system's true state. Let the true state of the UAV at discrete time k be x_k The observed output z_k of the airborne sensors can be uniformly expressed as:

$$\mathrm{z}_k = h(\mathrm{x}_k) + \mathrm{v}_k$$

Where $h(\cdot)$ represents the observation function, and v_k is the observation noise term, used to characterize uncertainties such as sensor error, environmental disturbances, and modeling incompleteness. This formula provides a unified modeling foundation for subsequent state estimation and multi-sensor fusion.

In UAV scenarios, v_k often does not satisfy the ideal independent and identically distributed Gaussian assumption. During actual flight, sensor noise often exhibits temporal correlation, state correlation, and obvious non-Gaussian characteristics. For example, the zero bias of an inertial sensor drifts slowly over time, resulting in a large number of outliers in visual observations, while lidar generates strong random scattering in rain, fog, or dust environments. Therefore, reasonable statistical modeling of sensor observation noise is one of the key issues in the design of UAV perception systems.

2.2. Random Modeling of Inertial Sensors

The Inertial Measurement Unit (IMU) is the most critical airborne sensor in a UAV, and its output directly determines the short-term observability of the UAV's attitude, speed, and position [25]. A typical IMU consists of a three-axis accelerometer and a three-axis gyroscope. Its measurement model is usually expressed as:

$$\tilde{\omega}_k = \omega_k + \mathrm{b}_k^g + \mathrm{n}_k^g, \tilde{\mathrm{a}}_k = \mathrm{a}_k + \mathrm{b}_k^a + \mathrm{n}_k^a$$

where ω_k and a_k are the true angular velocity and specific force, $\mathrm{b}_k^g, \mathrm{b}_k^a$ represent the zero-bias terms of the gyroscope and accelerometer, respectively, and $\mathrm{n}_k^g, \mathrm{n}_k^a$ are high-frequency random noise.

In statistical modeling, the zero-bias terms are usually treated as low-frequency random processes rather than fixed constants. Common modeling methods include random walk models or first-order Gaussian-Markov processes:

$$\mathrm{b}_{k+1} = \mathrm{b}_k + \mathrm{w}_k \text{ or } \dot{\mathrm{b}}(t) = -\frac{1}{\tau}\mathrm{b}(t) + \mathrm{w}(t)$$

where w_k represents the driving noise, and τ is the correlation time constant. This type of modeling can characterize the statistical properties of inertial sensor errors accumulating over time, and is an important prerequisite for the design of subsequent state estimation methods.

To quantify the statistical characteristics of inertial sensor noise, Allan variance analysis is widely used in the field of unmanned aerial vehicles (UAVs). Through statistical analysis of long-term static data, key noise parameters such as angle random walk and bias instability can be separated, thus providing a basis for modeling the process noise of filters.

2.3. Uncertainty Characteristics of Satellite Navigation

Global Navigation Satellite Systems (GNSS) provide absolute position information for UAVs. Their observation model can typically be expressed as:

$$\mathrm{z}_k^{gnss} = \mathrm{p}_k + \mathrm{v}_k^{gnss}$$

where p_k represents the UAV's position state, and v_k^{gnss} represents the measurement error. Compared to inertial sensors, GNSS observations exhibit significantly different statistical characteristics: their errors do not accumulate over time but are significantly affected by the environment.

In urban canyons, forests, or complex terrain environments, multipath effects and signal blockage can cause the GNSS error distribution to deviate from the Gaussian assumption, exhibiting heavy-tailed characteristics or even systematic biases. Furthermore, the GNSS update frequency is typically low, making it difficult to meet the navigation needs of UAVs alone under highly dynamic maneuvering conditions. This complementary nature of statistical characteristics is the theoretical basis for the fusion of GNSS and inertial sensors.

2.4. Statistical Characteristics of Visual and LiDAR

Visual cameras and LiDAR provide high-dimensional, dense, or semi-dense spatial information for UAV environmental perception, but their observation processes exhibit significant randomness and uncertainty.

For visual sensors, observations are typically performed as feature point or pixel-level measurements. Their statistical model can be abstracted as:

$$\mathrm{z}_k^{cam} = \pi(\mathrm{x}_k, \mathrm{m}) + \mathrm{v}_k^{cam}$$

where $\pi(\cdot)$ is the projection model, and m represents environmental feature points. Visual observation errors mainly originate from image noise, illumination variations, occlusion, and feature matching errors, resulting in a large number of outliers in the error distribution. In practical applications, the simple Gaussian assumption is insufficient to fully describe these error characteristics.

LiDAR observations are typically performed as distance or point cloud data. Their noise characteristics are affected by the ranging principle, reflectivity, and environmental conditions. In rainy, foggy, or dusty environments, laser scattering introduces a large number of random echo points, causing the point cloud data to exhibit highly non-ideal statistical distribution characteristics. These issues have led to the widespread application of robust statistical methods in lidar point cloud processing and SLAM.

2.5. Novel Sensors and Unconventional Modeling

In recent years, the emergence of novel airborne sensors has further enriched the statistical modeling problem of UAV perception systems. Neuromorphic sensors, represented by event cameras, output not continuously sampled signals, but asynchronous event streams triggered by brightness changes. From a statistical perspective, these sensors are modeled as inhomogeneous Poisson processes, where the probability of an event generation is proportional to the log-intensity gradient. Furthermore, the accurate fusion of these multi-modal sensors relies on precise calibration. Spatiotemporal calibration is fundamentally a statistical estimation problem, often solved by maximizing the joint likelihood of sensor measurements to recover extrinsic parameters and time offsets [26].

Compared to traditional frame sensors, event cameras have significant advantages in high-speed motion and extreme lighting conditions, but their data

Table 1: Statistical Comparison of Common UAV Sensors

Sensor	Key Error Sources	Statistical Noise Characteristics	Typical Modeling Approach
IMU	Bias drift, thermal noise, vibration	Time-varying bias accumulation, Gaussian white noise	Brownian Motion for bias; First-order Gauss-Markov process.
GNSS	Multipath, signal blockage	Non-Gaussian, heavy-tailed distributions, time-correlated errors	Student-t distribution or GMM to handle outliers.
Vision	Illumination change, mismatching	Data-dependent noise, frequent outliers.	Robust Cost Functions in optimization.
LiDAR	Scattering, reflectivity	Sparse outliers, multimodal distribution	Robust Kernels or Point-to-Plane probabilistic models.
Event Camera	Threshold noise, refractory period	Asynchronous point process, temporal sparsity	Inhomogeneous Poisson Process based on intensity changes.

sparsity and asynchronicity also pose new statistical challenges to state estimation and fusion algorithms [27]. The introduction of these sensors further highlights the necessity of a unified statistical understanding of UAV airborne perception problems. The specific statistical characteristics and corresponding modeling methods for these sensors are summarized as shown in Table **1**.

2.6. Summary

This chapter systematically analyzes common UAV airborne sensors from the perspective of statistical observation modeling, emphasizing the differences in noise characteristics, temporal correlation, and sources of uncertainty among different sensors. Through a unified statistical framework, it can be seen that regardless of the evolution of sensor physical mechanisms, the core issues always revolve around random observations and uncertainty modeling. This understanding lays the theoretical foundation for the state estimation and multi-sensor fusion methods based on statistical inference in the next chapter.

3. STATE ESTIMATION BASED ON STATISTICAL INFERENCE

Statistical observation modeling of UAV onboard sensors lays the foundation for the state estimation problem. This chapter systematically reviews commonly used state estimation methods in UAV navigation and perception from a statistical inference perspective, emphasizing their probabilistic assumptions, mathematical forms, and applicable boundaries.

3.1. Probabilistic Representation and Bayesian Framework

Let the state vector of the UAV system be:

$$\mathrm{x}_k \in \mathbb{R}^n$$

Its state evolution and observation process can be represented as a stochastic state-space model.

State transition model:

$$\mathrm{x}_k = f(\mathrm{x}_{k-1}, \mathrm{u}_{k-1}) + \mathrm{w}_{k-1}, \mathrm{w}_{k-1} \sim p(\mathrm{w})$$

Observation model:

$$\mathrm{z}_k = h(\mathrm{x}_k) + \mathrm{v}_k, \mathrm{v}_k \sim p(\mathrm{v})$$

The goal of UAV state estimation is to recursively solve for the posterior probability distribution:

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k})$$

3.2. Recursive Form of Bayesian Filtering

(1) Time Prediction:

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k-1}) = \int p(\mathrm{x}_k \mid \mathrm{x}_{k-1})\, p(\mathrm{x}_{k-1} \mid \mathrm{z}_{1:k-1})\, \mathrm{dx}_{k-1}$$

This integral characterizes the propagation of state uncertainty and is the statistical essence of the accumulation of inertial integral errors in UAVs.

(2) Measurement Update：

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k}) = \frac{p(\mathrm{z}_k \mid \mathrm{x}_k)\, p(\mathrm{x}_k \mid \mathrm{z}_{1:k-1})}{\int p(\mathrm{z}_k \mid \mathrm{x}_k)\, p(\mathrm{x}_k \mid \mathrm{z}_{1:k-1})\, \mathrm{dx}_k}$$

Where $p(\mathrm{z}_k \mid \mathrm{x}_k)$ is the likelihood function, directly determined by the sensor statistical observation model.

3.3. Linear Gaussian Case and Kalman Filtering

Assumptions: $f(\cdot)$, $h(\cdot)$ are linear, $\mathrm{w}_k, \mathrm{v}_k$为 are zero-mean Gaussian noise

The state model can be written as:

$$\mathrm{x}_k = \mathrm{F}_k \mathrm{x}_{k-1} + \mathrm{w}_{k-1}, \mathrm{w}_{k-1} \sim \mathcal{N}(0, \mathrm{Q}_{k-1})$$
$$\mathrm{z}_k = \mathrm{H}_k \mathrm{x}_k + \mathrm{v}_k, \mathrm{v}_k \sim \mathcal{N}(0, \mathrm{R}_k)$$

The posterior distribution remains Gaussian:

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k}) = \mathcal{N}(\hat{\mathrm{x}}_k, \mathrm{P}_k)$$

Prediction steps:

$$\hat{\mathrm{x}}_{k|k-1} = \mathrm{F}_k \hat{\mathrm{x}}_{k-1}$$
$$\mathrm{P}_{k|k-1} = \mathrm{F}_k \mathrm{P}_{k-1} \mathrm{F}_k^{\mathrm{T}} + \mathrm{Q}_{k-1}$$

Update steps:

$$\mathrm{K}_k = \mathrm{P}_{k|k-1} \mathrm{H}_k^{\mathrm{T}} (\mathrm{H}_k \mathrm{P}_{k|k-1} \mathrm{H}_k^{\mathrm{T}} + \mathrm{R}_k)^{-1}$$
$$\hat{\mathrm{x}}_k = \hat{\mathrm{x}}_{k|k-1} + \mathrm{K}_k (\mathrm{z}_k - \mathrm{H}_k \hat{\mathrm{x}}_{k|k-1})$$
$$\mathrm{P}_k = (\mathrm{I} - \mathrm{K}_k \mathrm{H}_k) \mathrm{P}_{k|k-1}$$

3.4. Nonlinear Systems and Extended Kalman Filter

UAV dynamics and sensor models are often highly nonlinear, therefore EKF is linearized through a first-order Taylor expansion:

$$\mathrm{F}_k = \frac{\partial f}{\partial \mathrm{x}} |_{\hat{\mathrm{x}}_{k-1}}, \mathrm{H}_k = \frac{\partial h}{\partial \mathrm{x}} |_{\hat{\mathrm{x}}_{k|k-1}}$$

EKF essentially assumes:

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k}) \approx \mathcal{N}$$

This approximation may introduce linearization errors under the conditions of high maneuverability and strong nonlinearity of UAVs, prompting the development of more robust methods.

3.5. Error State Kalman Filtering

To avoid directly linearizing the complete state, ESKF decomposes the state into:

$$\mathrm{x}_k = \bar{\mathrm{x}}_k \oplus \delta \mathrm{x}_k$$

Where: xk is the nominal state, and δ xk is the small error state.

The error state dynamics are approximated as a linear system:

$$\delta \dot{\mathrm{x}} = \mathrm{F}\, \delta \mathrm{x} + \mathrm{G}\, \mathrm{n}$$

The error covariance propagation is:

$$\mathrm{r}_k = \mathrm{z}_k - h(\bar{\mathrm{x}}_k)$$
$$\delta \hat{\mathrm{x}}_k = \mathrm{K}_k \mathrm{r}_k$$
$$\bar{\mathrm{x}}_k \leftarrow \bar{\mathrm{x}}_k \oplus \delta \hat{\mathrm{x}}_k$$

The statistical advantage of ESKF is that linearization always revolves around the zero-mean error, significantly improving numerical stability.

In high-dynamic UAV maneuvers, standard EKF operating on Euler angles may suffer from gimbal lock singularities. ESKF, by operating on the tangent space of the quaternion manifold (error state), avoids these singularities and maintains numerical stability even during aggressive flight maneuvers.

3.6. Non-Gaussian Case and Particle Filtering

When the noise distribution is significantly non-Gaussian or the system is highly nonlinear, the posterior distribution cannot be approximated by a single Gaussian distribution. Particle filtering approximates the posterior using the Monte Carlo method:

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k}) \approx \sum_{i=1}^{N} w_k^{(i)}\, \delta(\mathrm{x}_k - \mathrm{x}_k^{(i)})$$

Weight update:

$$w_k^{(i)} \propto w_{k-1}^{(i)}\, p(\mathrm{z}_k \mid \mathrm{x}_k^{(i)})$$

Resampling condition:

$$N_{\mathrm{eff}} = \frac{1}{\sum_{i=1}^{N} (w_k^{(i)})^2}$$

PF It has theoretical advantages in complex environment modeling, but its computational complexity limits its application in lightweight drones.

While computationally intensive, recent advances in GPU-accelerated parallel computing and efficient resampling strategies have made real-time Particle Filtering feasible for onboard UAV processors, particularly for non-Gaussian tasks like terrain-relative navigation.

3.7. Robust Estimation and Heavy-Tailed Noise Modeling

Outliers are prevalent in visual and LiDAR perception. Robust estimation minimizes the weighted residuals:

$$\min_{\mathrm{x}} \sum_i \rho(r_i)$$

where r_i is the observation residual, and $\rho(\cdot)$ is the robust loss function.

Huster Loss:

$$\rho(r) = \begin{cases} \frac{1}{2} r^2, & |\, r \,| \leq \delta \\ \delta(|\, r \,| - \frac{1}{2}\delta), & |\, r \,| > \delta \end{cases}$$

The negative log-likelihood corresponding to the Student-t distribution:

$$\rho(r) = \log\left(1 + \frac{r^2}{\nu}\right)$$

This type of method significantly improves robustness in SLAM and multi-sensor fusion.

3.8. Summary

This chapter systematically reviewed the development of UAV state estimation methods from a statistical inference perspective, from Kalman filtering under the linear Gaussian assumption to nonlinear, non-Gaussian, and robust estimation methods suitable for complex environments. It can be seen that the essential differences between different algorithms stem from their different assumptions about the form of state distribution and the statistical characteristics of noise. This understanding provides a theoretical foundation for the discussion of multi-sensor statistical fusion methods in the next chapter.

4. MULTI-SENSOR STATISTICAL FUSION AND JOINT PROBABILISTIC MODELING

In UAV systems, a single sensor often struggles to simultaneously meet the requirements of accuracy, robustness, and real-time performance in complex environments. Multi-sensor fusion, by introducing redundancy and complementary information, significantly improves state estimation and environmental perception performance. From a statistical perspective, the core issue of multi-sensor fusion lies in how to construct a joint probabilistic model among different observation sources and, based on this, perform consistent state inference.

4.1. Probabilistic Modeling Perspective of Multi-Sensor Fusion

Let the UAV system state be x_k, and at time k, it simultaneously receives observations from M sensors:

$$\mathrm{z}_k = \{\mathrm{z}_k^{(1)}, \mathrm{z}_k^{(2)}, \ldots, \mathrm{z}_k^{(M)}\}$$

In the most general case, the goal is to estimate the posterior distribution:

$$p(\mathrm{x}_k \mid \mathrm{z}_{1:k}^{(1)}, \mathrm{z}_{1:k}^{(2)}, \ldots, \mathrm{z}_{1:k}^{(M)})$$

If we assume that in a given state... Under the condition of x_k, if the observations of each sensor are independent, the joint likelihood can be decomposed as:

$$p(\mathrm{z}_k \mid \mathrm{x}_k) = \prod_{m=1}^{M} p(\, \mathrm{z}_k^{(m)} \mid \mathrm{x}_k)$$

The conditional independence assumption is the theoretical basis of most engineering fusion algorithms, but in practical UAV systems, this assumption often only holds approximately.

In real-world UAV platforms, the conditional independence assumption is often violated. for instance, high-frequency mechanical vibrations from rotors can simultaneously introduce correlated noise across both the IMU and the camera (via rolling shutter effects), requiring colored noise modeling or state augmentation to address the correlation.

4.2. Statistical Interpretation of Fusion Levels

From a statistical modeling perspective, multi-sensor fusion can be divided into different levels, each corresponding to different probability assumptions.

4.2.1. Data-Level Fusion

Data-level fusion directly constructs a joint likelihood function from the original observations:

$$\mathcal{L}(\mathrm{x}_k) = \prod_{m=1}^{M} p(\, \mathrm{z}_k^{(m)} \mid \mathrm{x}_k)$$

The corresponding Maximum A posteriori estimation (MAP) problem is:

$$\hat{\mathbf{x}}_k = \arg\max_{\mathbf{x}_k} \left[\log\, p(\mathbf{x}_k \mid \mathbf{z}_{1:k-1}) + \sum_{m=1}^{M} \log\; p(\mathbf{z}_k^{(m)} \mid \mathbf{x}_k) \right]$$

This form is suitable for tightly coupled... Widely used in GNSS/INS and VIO systems.

4.2.2. Feature-Level Fusion

In feature-level fusion, observations from different sensors are first mapped to a shared feature space $\mathbf{y}_k$:

$$\mathbf{y}_k^{(m)} = g_m(\mathbf{z}_k^{(m)})$$

Then a conditional model is constructed:

$$p(\mathbf{y}_k \mid \mathbf{x}_k)$$

This method is common in vision-LiDAR fusion, for example, using LiDAR depth to constrain the visual feature scale.

4.2.3. Decision-Level Fusion

Decision-level fusion assumes that each sensor has independently provided a state estimate $\hat{\mathbf{x}}_k^{(m)}$ and its covariance $\mathbf{P}_k^{(m)}$. Under the Gaussian assumption, the optimal linear fusion is:

$$\mathbf{P}_k^{-1} = \sum_{m=1}^{M} \left(\mathbf{P}_k^{(m)}\right)^{-1}$$

$$\hat{\mathbf{x}}_k = \mathbf{P}_k \sum_{m=1}^{M} \left(\mathbf{P}_k^{(m)}\right)^{-1} \hat{\mathbf{x}}_k^{(m)}$$

This method is computationally simple, but it is difficult to characterize the correlation between sensors.

4.3. Statistical Essence of Loosely Coupled and Tightly Coupled Fusion

4.3.1. Loosely Coupled Fusion

The loosely coupled method treats the state estimate output by a sensor (such as GNSS) as a pseudo-observation:

$$\mathrm{z}_k^{\text{pseudo}} = \hat{\mathrm{x}}_k^{\text{GNSS}}$$

and assumes its covariance is R_k^{GNSS}, with the corresponding likelihood function being:

$$p(z_k^{\text{pseudo}} \mid x_k) = \mathcal{N}(x_k, R_k^{\text{GNSS}})$$

From a statistical perspective, the loosely coupled method implicitly assumes that the high-level estimates are conditionally independent and that information loss is negligible.

4.3.2. Tightly Coupled Fusion

The tightly coupled method directly uses the original observations to construct the joint likelihood. For example, in tightly coupled GNSS/INS:

$$z_k^{\text{GNSS}} = h(x_k) + v_k$$

its joint posterior is:

$$p(x_k \mid z_k^{\text{IMU}}, z_k^{\text{GNSS}}) \propto p(z_k^{\text{GNSS}} \mid x_k) p(x_k \mid z_k^{\text{IMU}})$$

This method still provides effective constraints when observations degrade (e.g., insufficient satellite count), and has higher statistical efficiency.

4.4. Visual-Inertial Joint Probabilistic Modeling

Visual-inertial odometry achieves robust estimation of scale and rapid motion by jointly modeling visual observations and IMU pre-integration.

Let the visual feature observation residual be:

$$r_k^{\text{cam}} = z_k^{\text{cam}} - \pi(x_k, m$$

The IMU pre-integration residual is:

$$r_k^{\text{imu}} = \hat{\alpha}_{ij} - \alpha(x_i, x_j)$$

4.5. Vision-LiDAR Joint Modeling

In vision-LiDAR fusion, the joint probability model can be written as:

$$p(x_k, m \mid z_k^{\text{cam}}, z_k^{\text{lidar}}) \propto p(z_k^{\text{cam}} \mid x_k, m) p(z_k^{\text{lidar}} \mid x_k, m) p(x_k)$$

The corresponding optimization objective function is:

$$\min \sum_i \rho_{\text{cam}} (\| r_i^{\text{cam}} \|) + \sum_j \rho_{\text{lidar}} \left(\| r_j^{\text{lidar}} \|\right)$$

Where $\rho(\cdot)$ is the robust loss function, used to suppress outliers.

4.6. Information Filtering and Distributed Fusion

In multi-UAV or distributed sensing systems, information in a more formalized form is more advantageous. Define the information matrix:

$$\Lambda_k = P_k^{-1}, \eta_k = P_k^{-1}\hat{x}_k$$

Information fusion can be directly achieved through summation:

$$\boldsymbol{\Lambda}_k = \sum_{m=1}^{M} \boldsymbol{\Lambda}_k^{(m)}, \boldsymbol{\eta}_k = \sum_{m=1}^{M} \boldsymbol{\eta}_k^{(m)}$$

This form is particularly suitable for communication-constrained or asynchronous update scenarios.

4.7. Statistical Fault Detection and Integrity

From a statistical perspective, sensor failure detection is modeled as hypothesis testing. Methods such as Chi-square tests on the normalized innovation squared (NIS) or residual monitoring are used to detect statistical anomalies, allowing the fusion filter to isolate faulty sensors and maintain integrity. This mechanism is critical for safety-critical UAV operations to prevent catastrophic divergence due to sensor malfunctions.

4.8. Summary

This chapter systematically analyzed UAV multi-sensor fusion methods from the perspective of joint probabilistic modeling, revealing the essential differences in statistical assumptions and information utilization efficiency among different fusion strategies. It can be seen that multi-sensor fusion is not a simple data superposition, but a problem of consistent modeling and inference of multi-source uncertainties. This understanding lays the foundation for the discussion of high-dimensional perception and statistical learning methods in the next chapter.

5. STATISTICAL LEARNING AND APPLICATIONS OF UNCERTAINTY PERCEPTION

With the increasing number of onboard sensors and the growing dimensionality of perception in UAVs, perception problems are gradually expanding from low-dimensional state estimation to high-dimensional environmental understanding and semantic modeling. In this context, traditional statistical inference methods relying on explicit probability models and linearization assumptions face modeling difficulties and computational bottlenecks when dealing with complex scenes and high-dimensional observations. Statistical learning methods, especially the combination of deep learning and Bayesian learning, provide a new modeling paradigm for UAV perception systems.

It should be noted that statistical learning methods are not a replacement for the classical statistical inference framework, but rather an extension of it in high-dimensional, strongly nonlinear scenarios. Understanding this is crucial for reasonably evaluating its role in UAV systems.

5.1. Statistical Interpretation of Deep Learning

In UAV vision and multimodal perception tasks, deep neural networks are commonly used for object detection, semantic segmentation, and feature extraction. From a statistical perspective, deep models can be viewed as function approximators of complex conditional probability distributions. For example, in visual perception, neural networks can approximate the mapping from observation z to latent variable y:

$$\mathrm{y} = f_{\theta}(\mathrm{z})$$

where the parameter \theta is learned through maximum likelihood or empirical risk minimization.

In UAV scenarios, deep models are often embedded in traditional statistical frameworks, such as as part of observation models, feature extraction modules, or data association mechanisms. This hybrid paradigm of "statistical inference + learning model" has become the mainstream design approach for current UAV perception systems.

5.2. Uncertainty Perception and Probabilistic Learning

In safety-critical UAV applications, relying solely on point estimation outputs for perception results is insufficient to meet system reliability requirements. Uncertainty-aware perception has gradually become a research focus, aiming to provide a reliability measure for model predictions.

From a statistical learning perspective, uncertainty can generally be divided into two categories:

Aleatoric Uncertainty: Caused by sensor noise and environmental randomness;

Epistemic Uncertainty: Caused by model structure and the finiteness of training data.

To characterize these uncertainties, researchers have proposed various methods, including Bayesian neural networks, Monte Carlo Dropout, and deep model ensembles. These methods sample model parameters or output distributions, enabling deep models to output predictive distributions rather than single estimates, thus providing statistically significant risk information for subsequent state estimation, path planning, and control.

In UAV perception systems, uncertainty estimation has been used for tasks such as dynamic obstacle avoidance, risk-constrained path planning, and sensor degradation detection, demonstrating the practical value of statistical learning methods at the engineering level.

Practically, Monte Carlo (MC) Dropout approximates the posterior distribution by performing multiple stochastic forward passes during inference. Similarly, Deep Ensembles train multiple independent networks to capture epistemic uncertainty, providing a variance estimate that is critical for fusing learning-based outputs with traditional filters.

5.3. Optimization Perspective of High-Dimensional Perception

In tasks such as visual SLAM, LiDAR SLAM, and semantic mapping, the state estimation problem is often transformed into a large-scale nonlinear optimization problem. From a statistical perspective, this type of problem can be uniformly interpreted as a maximum a posteriori (MAP) estimation problem:

$$\hat{\mathrm{x}} = \arg\max_{\mathrm{x}} \; \log\, p(\mathrm{z} \mid \mathrm{x}) + \log\, p(\mathrm{x})$$

Where, the prior term $p(\mathrm{x})$ reflects the motion model and physical constraints, while the likelihood term $p(\mathrm{z} \mid \mathrm{x})$ is given by the sensor observation model or learning model. In this framework, deep learning methods often play the role of likelihood modeling or feature association, rather than independently completing the entire inference process.

This unified understanding of learning methods from a statistical optimization perspective helps avoid simplifying UAV perception problems into purely data-driven tasks and also provides theoretical support for the interpretability and stability of algorithms.

5.4. Statistical Learning Challenges for Novel Sensors

The introduction of novel airborne sensors has further expanded the application boundaries of statistical learning methods in UAVs. Neuromorphic sensors, such as event cameras, output asynchronous event streams instead of regularly sampled continuous signals. This type of data is naturally suitable for description using point process and probabilistic graphical models, posing new challenges to statistical learning methods.

In research on the fusion of event vision with traditional vision or inertial sensors, learning models are often used to estimate the event generation process or assist in data association, while state estimation and fusion still rely on probabilistic inference frameworks. This design approach of "statistical model-led, learning model-assisted" demonstrates strong versatility in the application of novel sensors.

5.5. Limitations and Engineering Considerations

Although statistical learning methods show significant advantages in perception accuracy and expressive power, their application in UAV systems still faces several challenges, including model generalization ability, training data dependence, and computational resource consumption. Furthermore, the statistical assumptions of deep models are often implicit in the training process, lacking explicit physical and probabilistic interpretations, which to some extent limits their direct application in high-security scenarios.

Therefore, the current research trend is not to completely replace traditional statistical inference with statistical learning methods, but rather to explore the complementarity and integration of the two, so as to achieve a balance between performance, robustness, and interpretability in UAV perception systems.

A critical statistical challenge is Out-of-Distribution (OOD) detection. Deep models trained on clean data often yield overconfident incorrect predictions when facing unknown environmental disturbances (e.g., smoke or glare). Furthermore, the lack of adversarial robustness poses security risks, necessitating rigorous statistical verification.

5.6. Summary

This chapter provides a general overview of the development of UAV airborne sensor perception methods from the perspective of statistical learning and uncertainty perception. It can be seen that statistical learning methods mainly play a role in high-dimensional modeling and complex mapping in UAV perception systems, while the statistical inference framework remains the core foundation for achieving consistent estimation and risk control. The deep integration of the two constitutes an important research direction for current and future UAV perception systems.

6. SUMMARY AND OUTLOOK

6.1. Summary

This paper systematically reviews the theoretical foundations, methodological evolution, and development trends of UAV airborne sensor research from a statistical perspective. Unlike traditional reviews that focus on sensor type or single algorithm, this paper places the UAV perception problem within a unified framework of stochastic observation and statistical inference, providing a holistic analysis of airborne sensor data modeling, uncertainty sources, and multi-source fusion mechanisms.

By reviewing the statistical characteristics of inertial sensors, satellite navigation, vision, lidar, and novel neuromorphic sensors, it can be seen that the core challenge facing UAV perception systems is not the insufficient accuracy of a single sensor, but rather the superposition and propagation of multiple uncertainties across time, space, and modal dimensions. To address this issue, this paper systematically reviews state estimation methods based on Bayesian inference, analyzing the applicability and limitations of Kalman filtering, error state filtering, particle filtering, and robust statistical methods under different assumptions.

Regarding multi-sensor fusion, this paper compares loosely coupled and tightly coupled fusion strategies from the perspective of joint probabilistic modeling, pointing out that the essential difference in fusion effects stems from different approaches to handling observation correlation and information utilization efficiency. Furthermore, as perception tasks expand to higher dimensions and semantic levels, statistical learning methods have gradually become an important component of UAV perception systems. However, their engineering applications still rely on statistical inference frameworks to explicitly characterize and constrain uncertainty.

Overall, the development history of UAV onboard sensors shows that statistical modeling and inference methods have always been the key link between sensor hardware and autonomous decision-making capabilities. Regardless of how perception modalities evolve, the core issue always revolves around uncertainty.

6.2. Future Research Directions

Although existing research has made significant progress in UAV onboard sensor modeling and fusion, several research directions still warrant in-depth exploration in complex real-world environments.

First, uncertainty perception and risk-constrained decision-making will become an important development direction for UAV systems. Future research needs to further explicitly introduce uncertainties in sensor and state estimation into the path planning, control, and task decision-making layers, enabling UAVs to make risk-controlled autonomous decisions under imperfect perception conditions.

Second, joint statistical modeling of high-dimensional heterogeneous sensors still faces the trade-off between modeling complexity and computational feasibility. How to construct consistent probabilistic models for multimodal, high-dimensional observations while ensuring real-time performance is one of the key factors restricting the further development of UAV perception systems.

Third, the deep integration of statistical inference methods and statistical learning models is expected to achieve a better balance between performance and interpretability. By introducing physical priors, structural constraints, and probabilistic interpretations, learning models can better serve UAV perception systems, rather than existing as isolated black-box modules.

Fourth, Digital Twins and Simulation-based Inference will play a pivotal role. High-fidelity simulations allow for the generation of massive datasets covering rare "long-tail" events, enabling the training and validation of statistical models against ground truth that is unobtainable in physical flight.

Finally, Edge AI and Lightweight Inference are crucial. Future algorithms must balance statistical rigor with SWaP (Size, Weight, and Power) constraints, utilizing hardware-aware optimization (e.g., quantization, pruning) to run complex probabilistic models on embedded UAV processors.

With the development of edge computing and integrated sensing-computing architectures, lightweight, online-updable statistical inference methods will become an important research direction in UAV onboard system design. These methods need to achieve stable and reliable uncertainty modeling and inference under limited computing power and power consumption.

Research on UAV onboard sensors is not only a competition of sensor hardware and algorithm performance, but also a continuous deepening of the understanding and handling capabilities of uncertainty. A unified examination of different perception technologies from a statistical perspective helps clarify the applicable boundaries of existing methods and provides a theoretical basis for the design of future autonomous UAV perception systems. Integrating statistical methods with novel sensors empowers safe autonomy. Robust perception is the cornerstone of Intelligent Aeronautical Systems, enabling collision avoidance and future UAV Traffic Management (UTM) integration.

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Received on 16-11-2025 Accepted on 15-12-2025 Published on 28-12-2025

https://doi.org/10.65904/3083-3450.2025.01.06