

EFG-EKF-SLAM: ENTROPY-GATED INNOVATION FOR FEATURE-AWARE EXTENDED KALMAN SLAM

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Abstract: In this paper, we introduce an innovative improvement to the traditional Extended Kalman Filter-based Simultaneous Localization and Mapping framework, called Entropy-Gated Feature-Aware EKF-SLAM. Our approach presents a flexible information-theoretic mechanism that adjusts the impact of each landmark observation in real-time, depending on the historical entropy of its measurement distribution. Traditional EKF-SLAM assumes that all observations are equally trustworthy based on noise models. In contrast, our approach assesses long-term measurement consistency using rolling entropy profiles, which allows for per-landmark trust gating during the innovation update. Rather than directly scaling the innovation term, the proposed method adapts the effective measurement noise covariance of each landmark according to its entropy-derived trust level, ensuring statistical consistency within the Kalman filtering framework. This probabilistically grounded formulation enables the filter to discount features that are ambiguous, noisy, or aliased, while preserving reliable covariance estimation and emphasizing landmarks that are historically stable and informative. This entropy-aware gate is integrated directly into the EKF correction equations, maintaining the prediction model intact and ensuring computational efficiency is preserved. A complete mathematical derivation supports theoretical development, and we present a detailed simulation in MATLAB featuring a mobile robot navigating a 2D environment with five landmarks. Results from experiments show enhanced accuracy in trajectory and greater robustness when faced with perceptual ambiguity and dynamic sensor noise. This change represents an important advancement in adaptive uncertainty modeling in filtering-based SLAM frameworks.

Key words: EKF-SLAM, Entropy-Gated Update, Measurement Uncertainty, Feature Trust, Information-Theoretic SLAM, Landmark Filtering, Mobile Robots, Robust Localization

1. INTRODUCTION

To write Simultaneous Localization and Mapping (SLAM) continues to be a fundamental ability in autonomous robotics, allowing mobile agents to traverse and comprehend unfamiliar environments without existing maps. Among the most examined frameworks, the Extended Kalman Filter-based SLAM (EKF-SLAM) formulation remains a dependable and computationally efficient method for state estimation, especially in structured or somewhat dynamic settings. By keeping a joint Gaussian distribution for both robot pose and landmark positions, EKF-SLAM successfully propagates uncertainty while integrating sensor feedback through a prediction-correction cycle [1]. Nonetheless, in spite of its theoretical elegance and practical success, classical EKF-SLAM faces several limitations that impede its application in more complex real-world scenarios. The primary considerations include the assumptions of Gaussian noise, static landmarks, and consistent, independent sensor observations. In settings characterized by perceptual aliasing, occlusions, dynamic objects, or non-stationary noise patterns, the performance of the filter diminishes because of inadequate data association and fragile update mechanisms. Most importantly, EKF-SLAM considers all observed features in the correction step, depending only on the current residual and previous covariance structure to modify the belief state [2]. Recent attempts to address

these vulnerabilities have investigated the combination of learning-based perception, strong filtering, and information-theoretic planning. For example, deep learning has been utilized to improve loop closure detection and landmark recognition, thereby enhancing map consistency in settings with varying appearances [3][4]. At the same time, strong SLAM algorithms have implemented gating mechanisms that utilize Mahalanobis distance or residual norm thresholds to remove outliers [5]. Simultaneously, entropy and mutual information have been utilized in active SLAM and exploration, where actions are selected to enhance expected information gain [6][7]. Although these directions show potential, they either separate the sensing and filtering processes or utilize information-theoretic reasoning only at the planning layer, without modifying the internal estimation dynamics of EKF-SLAM. It is important to note that only a limited number of methods have tackled the issue of dynamically adjusting the impact of specific observations in the EKF update equation according to their long-term usefulness. Most SLAM frameworks operate under the assumption that an observation, when it is geometrically consistent and falls within noise limits, holds equal utility. This assumption fails in situations where certain landmarks yield unreliable or unclear measurements over time, like reflective surfaces, textureless walls, or recurring patterns. An adaptive strategy would assess the historical impact of each feature on the estimation process and adjust its influence as needed. We propose an innovative approach that integrates a lightweight but

robust information-theoretic correction scheme into the traditional EKF framework. Our approach calculates rolling entropy profiles based on landmark measurements and employs them to adjust the innovation term during the correction phase. This entropy-aware gating mechanism allows the filter to prioritize features that reliably yield informative, low-entropy measurements, while diminishing the influence of those that display high uncertainty or perceptual ambiguity. In contrast to outlier rejection methods that depend on rigid thresholds, our approach offers a continuous trust score based on information theory, thereby maintaining essential weak signals and preventing filter degradation. This approach connects robust estimation with information-theoretic filtering, introducing a novel dimension of adaptivity to EKF-SLAM. By evaluating not only the accuracy of a measurement but also its historical significance, we improve the resilience and reliability of SLAM in practical applications. Our research aligns with contemporary trends in uncertainty-aware, learning-informed SLAM, while preserving compatibility with traditional filter logic and real-time requirements. This paper presents a new SLAM design that adds an information-based improvement to the traditional Extended Kalman Filter (EKF) system, with the goal of bettering how mobile robots navigate in unclear environments. Our principal contribution is the incorporation of an entropy-aware innovation gating mechanism that assesses the temporal consistency of landmark observations through rolling measurement entropy profiles. Unlike traditional methods that only rely on fixed noise models or immediate differences, our approach changes how much each observation affects the EKF update based on how useful it has been over time. This adaptive trust model allows the SLAM system to ignore noisy, confusing, or unreliable features while focusing on landmarks that have performed well over time. The outcome is a more robust estimation process that markedly diminishes drift and enhances resilience to visual aliasing and sensor deterioration. We execute and assess our system through simulation, utilizing a differential-drive robot functioning in a two-dimensional environment with numerous landmarks. The results show major improvements in position accuracy, landmark dependability, and overall map quality compared to traditional EKF-SLAM. This study highlights the potential of using information-theoretic observability in probabilistic filtering to create more flexible and dependable systems for autonomous navigation. The subsequent sections of this paper follow this structure: Section 2 looks at important research on improvements to EKF-SLAM, strong estimation methods, and navigation guided by entropy. Section 3 summarizes the traditional EKF-SLAM framework, encompassing its state and measurement models. Section 4 delineates our proposed Entropy-Gated Feature-Aware EKF-SLAM (EFG-EKF-SLAM), accompanied by comprehensive mathematical formulation and theoretical justification. Section 5 delineates the simulation configuration, implementation specifics, and evaluation criteria while also analyzing the experimental outcomes. Ultimately, Section 6 concludes the paper and delineates prospective avenues for future research.

2. RELATED WORKS

The evolving landscape of SLAM research reflects a growing interest in bridging classical probabilistic estimation with modern machine learning and information-theoretic models. While the Extended Kalman Filter-based SLAM (EKF-SLAM) framework is still popular because it is efficient and well-supported by theory, it has ongoing challenges—especially with issues like confusing similar objects, dealing with moving scenes, and ensuring accurate measurements. A major line of enhancement has focused on integrating

deep learning to support tasks like visual understanding and data association. CNN-based systems such as DeepVO [8] and DROID-SLAM [9] have demonstrated significant improvements in pose estimation accuracy through end-to-end learning. These systems often replace or augment parts of the SLAM pipeline with differentiable neural components. However, they are typically dataset-dependent and computationally intensive, limiting their applicability in real-time, resource-constrained platforms. Moreover, they decouple perception from state estimation, treating learned features as static inputs to a separate filtering or optimization layer. In response, hybrid SLAM architectures have emerged, combining learning-based perception with classical filters like EKF or particle filters. Some examples are neural modules that help with recognizing when a robot has returned to a previous location [10], understanding the environment [11], and estimating distances [12], while traditional probabilistic filters still handle the tracking of the robot's position. A notable case is CNN-enhanced EKF-SLAM [13], where deep visual features inform landmark observations. While promising, such systems typically treat learned features as fixed priors, lacking mechanisms for adaptive trust during the filtering process. Another research avenue has investigated information-theoretic methodologies in SLAM, particularly regarding active exploration. Methods utilizing entropy and mutual information have been employed to direct motion planning, allowing robots to traverse environments in a manner that optimizes comprehension of their surroundings [14][15]. Nonetheless, these informational measures are typically implemented at the planning stage and do not directly influence the EKF's internal correction phase, rendering the estimation process susceptible to erroneous or ambiguous observations. To make sure the measurements are reliable, strong filtering methods like Mahalanobis gating, residual norm tests, and outlier rejection have been recommended to prevent the EKF from being affected by incorrect sensor data [16][17]. These methods are generally binary and threshold-dependent, jeopardizing the acceptance of potentially valuable information. Significantly, they also lack memory, perceiving each observation as an isolated event without deriving insights from historical patterns. Recently, adaptive observation modeling has been introduced using methods such as heteroscedastic Gaussian processes and time-varying noise scaling [18]. Even though they can manage changing uncertainty, these methods often require a lot of computing power and may need the model to be updated or retrained regularly. Additionally, they continue to depend on Gaussian assumptions and do not clearly monitor or utilize long-term observation statistics for each landmark. In 2024, Chen and his team created an EKF-SLAM model that used special features to change the Kalman gain based on the current randomness of sensor data [19]. This method improved resilience to unpredictable data but failed to account for time-related patterns, rendering it susceptible to brief variations. In 2025, Li and Kumar presented Temporal Entropy SLAM, which employed rolling entropy profiles to reduce the influence of observations from unstable landmarks [20]. Although conceptually aligned with our work, their entropy computation functioned outside the EKF loop, necessitating post-processing and extra logic. They also failed to assess performance under landmark aliasing, which is a frequent failure point in real-world deployments. At the same time, Garcia and others developed a system for linking data using information theory, applying mutual information to improve loop closure and feature matching [21]. While successful in visually repetitive settings, the approach depended on pretrained descriptors and was unable to adaptively adjust measurement trust throughout the filtering process. These recent initiatives highlight the significance of incorporating

information-aware mechanisms into SLAM pipelines. Nonetheless, many continue to regard entropy as an external factor, fail to model temporal consistency, or add computational complexity that is not appropriate for real-time applications.

Beyond Gaussian-assumed EKF formulations, recent research has explored state estimation under non-Gaussian noise and highly uncertain sensing conditions. For instance, a nonlinear non-Gaussian filtering framework built on a Gaussian noise model with jump assumptions has demonstrated increased robustness against abrupt process and measurement disturbances, particularly useful in multipath-affected environments [22]. Similarly, a Gaussian mixture unscented Rauch–Tung–Striebel smoothing framework has been proposed to improve trajectory reconstruction accuracy in scenarios with significant nonlinearities and non-Gaussian uncertainties [23]. Furthermore, distributed maneuvering vehicle tracking using ultra-wideband observations has been shown to provide reliable positioning in convoluted indoor environments where vision-only SLAM can degrade [24]. These works address robustness at the uncertainty modeling level, whereas the proposed EFG-EKF-SLAM framework introduces complementary benefits by adaptively modulating measurement trust within the classical EKF structure using information-theoretic consistency. Integrating entropy-aware trust gating with mixture-based filters or smoothing approaches represents a promising direction for future research.

The EFG-EKF-SLAM we suggest adds a simple, per-landmark entropy profile right into the EKF innovation step, allowing the filter to adjust how much each measurement matters based on its long-term usefulness. This combination makes the system better at handling noise, confusion, and similar environments—without needing outside classifiers, learning models, or complicated preprocessing. Unlike nonlinear gating methods that rely on instantaneous residual thresholds (e.g., Mahalanobis gating), the proposed approach uses temporal information-theoretic consistency rather than geometric outlier detection. Therefore, it does not directly compete with residual-based gating but complements it by modeling long-term landmark reliability. To help clarify our contribution, Table 1 shows a comparison of recent SLAM methods, focusing on their main innovations, limitations, and how they differ from our proposed Entropy-Gated Feature-Aware EKF-SLAM (EFG-EKF-SLAM). This table highlights that, although numerous works have investigated learning-based perception, robust filtering, or information-theoretic reasoning, none have closely integrated long-term, entropy-based trust modulation directly into the EKF correction step, as we suggest.

Tab. 1. Summary of Related Work in SLAM Research

Ref (Year)	Approach	Core Contribution	Limitation	Differences from EFG-EKF-SLAM
[8] (2017)	DeepVO (CNN-based VO)	End-to-end visual odometry using deep networks	Dataset-specific; replaces classical filter	EFG-EKF-SLAM keeps EKF, adds entropy-based innovation modulation
[9] (2021)	DROID-SLAM	Dense optimization and learned correspondence	High compute cost; unsuitable for embedded systems	EFG-EKF-SLAM is lightweight and filter-based

[10] (2022)	Neural Loop Closure	CNN-based image matching for loop closure	Loop closure only; not part of estimation loop	EFG-EKF-SLAM affects EKF core equations
[11] (2021)	Semantic SLAM	Integrates semantic segmentation into SLAM	Segmentation error can propagate; lacks dynamic trust	EFG-EKF-SLAM is geometry-based and adaptively trust-aware
[12] (2017)	SfmLearner	Unsupervised depth and pose estimation	Scale ambiguity; no uncertainty modeling	EFG-EKF-SLAM maintains probabilistic foundation
[13] (2023)	CNN-Enhanced EKF-SLAM	Merges learned features with EKF updates	Static trust in features; no dynamic weighting	EFG-EKF-SLAM adjusts influence via per-landmark entropy
[14] (2005)	Info-Gain for Exploration	Map-level entropy maximization for planning	Planning-only; no effect on correction step	EFG-EKF-SLAM modifies the EKF correction itself
[15] (2013)	Mutual Information Control	Uses mutual info to plan sensing actions	Control layer only; filtering remains unchanged	EFG-EKF-SLAM integrates info theory in EKF update
[16] (2018)	Mahalanobis Gating	Outlier rejection using residual norms	Hard threshold; binary acceptance	EFG-EKF-SLAM allows continuous entropy-based trust modulation
[17] (2019)	Visual-Inertial Filtering	Robust pose from camera + IMU	Requires inertial sensors; no entropy modeling	EFG-EKF-SLAM is purely visual, entropy-driven
[18] (2021)	Adaptive Covariance Modeling	Learns time-varying noise characteristics	Computationally heavy; complex model fitting	EFG-EKF-SLAM is simpler, with direct entropy scaling
[19] (2024)	Entropy-Gated EKF-SLAM	Adjusts Kalman gain using instantaneous entropy	No temporal history; sensitive to short-term noise	EFG-EKF-SLAM uses rolling entropy profiles per landmark
[20] (2025)	Temporal Entropy SLAM	Tracks entropy trends over time for landmark gating	Post-processing gate; not directly embedded in EKF update	EFG-EKF-SLAM integrates entropy modulation within the EKF innovation step
[21] (2025)	Mutual Information-Based Data Association	Uses MI to improve loop closure and feature matching	Relies on pretrained descriptors; high compute	EFG-EKF-SLAM is real-time and doesn't require learning or training

3. EKF-SLAM FRAMEWORK

Simultaneous Localization and Mapping (SLAM) is the problem where a robot builds a map of an unknown environment while simultaneously estimating its pose within that map. The Extended Kalman Filter (EKF) SLAM provides a solution when assuming:

Gaussian noise in motion and measurement, and small nonlinearities that can be approximated linearly.

3.1. State Representation

Let Define $\mathbf{x}_t = [x_t, y_t, \theta_t]^T$ the robot pose at time t , $\mathbf{m}_i = [m_{ix}, m_{iy}]^T$ the Coordinates of landmark i , $\mathbf{m} = [\mathbf{m}_1^T, \mathbf{m}_2^T, \dots, \mathbf{m}_N^T]^T$ the Full map, and $\mathbf{y}_t = [\mathbf{x}_t^T, \mathbf{m}^T]^T$ the Complete system state with $\mathbf{y}_t \in \mathbb{R}^{3+2N}$. The Differential drive robot motion is described by the equation (1).

$$\mathbf{x}_t = g(\mathbf{x}_{t-1}, \mathbf{u}_t) + \mathbf{w}_t \quad (1)$$

where $\mathbf{u}_t = [v_t, \omega_t]^T$ is the control input: translational and rotational velocities, and $\mathbf{w}_t \sim \mathcal{N}(0, \mathbf{Q}_t)$ is the process noise. A common motion model for differential drive robots can be given by equation (2).

$$\begin{aligned} x_t &= x_{t-1} + v_t \Delta t \cos(\theta_{t-1}) \\ y_t &= y_{t-1} + v_t \Delta t \sin(\theta_{t-1}) \\ \theta_t &= \theta_{t-1} + \omega_t \Delta t \end{aligned} \quad (2)$$

In vector form, equation (2) becomes equation (3):

$$\mathbf{x}_t = \begin{bmatrix} x_{t-1} + v_t \Delta t \cos(\theta_{t-1}) \\ y_{t-1} + v_t \Delta t \sin(\theta_{t-1}) \\ \theta_{t-1} + \omega_t \Delta t \end{bmatrix} + \mathbf{w}_t \quad (3)$$

Since the map \mathbf{m} is static, so:

$$\mathbf{m}_t = \mathbf{m}_{t-1} \quad (4)$$

Thus, the full motion model for \mathbf{y}_t is:

$$\mathbf{y}_t = \begin{bmatrix} g(\mathbf{x}_{t-1}, \mathbf{u}_t) \\ \mathbf{m}_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{w}_t \\ \mathbf{0} \end{bmatrix} \quad (5)$$

3.2. Measurement Model

Assuming range and bearing sensors, measurement to landmark i is:

$$\begin{aligned} r_i &= \sqrt{(m_{ix} - x_t)^2 + (m_{iy} - y_t)^2} \\ \phi_i &= \arctan2(m_{iy} - y_t, m_{ix} - x_t) - \theta_t \end{aligned} \quad (6)$$

Thus:

$$\mathbf{z}_{i,t} = \begin{bmatrix} r_i \\ \phi_i \end{bmatrix} + \mathbf{v}_{i,t} \quad (7)$$

where $\mathbf{v}_{i,t} \sim \mathcal{N}(0, \mathbf{R}_t)$. Generalizing to multiple observations:

$$\mathbf{z}_t = h(\mathbf{y}_t) + \mathbf{v}_t \quad (8)$$

3.3. EKF-SLAM Prediction Step

Using the motion model:

$$\boldsymbol{\mu}_{t|t-1} = \begin{bmatrix} g(\boldsymbol{\mu}_{t-1}^x, \mathbf{u}_t) \\ \boldsymbol{\mu}_{t-1}^m \end{bmatrix} \quad (9)$$

where $\boldsymbol{\mu}^x$ and $\boldsymbol{\mu}^m$ denote the robot and map parts respectively. The Jacobian \mathbf{G}_t of g with respect to the \mathbf{x} is:

$$\mathbf{G}_t = \left. \frac{\partial g}{\partial \mathbf{x}} \right|_{\boldsymbol{\mu}_{t-1}^x, \mathbf{u}_t} \quad (10)$$

Explicitly:

$$\mathbf{G}_t = \begin{bmatrix} 1 & 0 & -v_t \Delta t \sin(\theta_{t-1}) \\ 0 & 1 & v_t \Delta t \cos(\theta_{t-1}) \\ 0 & 0 & 1 \end{bmatrix} \quad (11)$$

Augment with map (since map is static):

$$\mathbf{F}_x = [\mathbf{I}_3 \quad \mathbf{0}_{3 \times 2N}] \quad (12)$$

Thus:

$$\boldsymbol{\Sigma}_{t|t-1} = \mathbf{F}_x^T \mathbf{G}_t \mathbf{F}_x \boldsymbol{\Sigma}_{t-1} \mathbf{F}_x^T \mathbf{G}_t^T \mathbf{F}_x + \mathbf{F}_x^T \begin{bmatrix} \mathbf{Q}_t & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{F}_x \quad (13)$$

3.4. EKF-SLAM Correction Step

The Extended Kalman Filter (EKF) correction step in Simultaneous Localization and Mapping (SLAM) serves to refine the robot's belief about its pose and the map using incoming sensor measurements. Mathematical development proceeds as follows: First, given a predicted mean $\boldsymbol{\mu}_{t|t-1}$ and predicted covariance $\boldsymbol{\Sigma}_{t|t-1}$ after the motion update, we use the sensor model to compute the expected measurement $\hat{\mathbf{z}}_t$, which represents what the robot expects to observe, given its current predicted state. This expected measurement is evaluated by passing the predicted state through the observation function $h(\cdot)$:

$$\hat{\mathbf{z}}_t = h(\boldsymbol{\mu}_{t|t-1}) \quad (14)$$

The next step involves computing the innovation, also known as the measurement residual, which quantifies the difference between the actual received measurement \mathbf{z}_t and the expected measurement:

$$\mathbf{r}_t = \mathbf{z}_t - \hat{\mathbf{z}}_t \quad (15)$$

This innovation vector captures the inconsistency between prediction and observation and will later be used to correct the state estimate. Since the observation function $h(\cdot)$ is generally nonlinear (for example, involving range and bearing calculations), we must linearize it to apply the Kalman update equations. This is achieved by computing the Jacobian matrix \mathbf{H}_t , which consists of partial derivatives of h with respect to the full state vector \mathbf{y} . For a single landmark i , the Jacobian $\mathbf{H}_{i,t}$ is given by:

$$\mathbf{H}_{i,t} = \frac{\partial h_i}{\partial \mathbf{y}} \quad (16)$$

where h_i is the function predicting the observation of landmark i .

Explicitly, the form of $\mathbf{H}_{i,t}$ for a 2D landmark and robot pose can be written as:

$$\mathbf{H}_{i,t} = \begin{bmatrix} \frac{-(m_{ix}-x_t)}{r_i} & \frac{-(m_{iy}-y_t)}{r_i} & 0 & \dots & \frac{m_{ix}-x_t}{r_i} & \frac{m_{iy}-y_t}{r_i} & \dots \\ \frac{m_{iy}-y_t}{r_i^2} & \frac{-(m_{ix}-x_t)}{r_i^2} & -1 & \dots & \frac{-(m_{iy}-y_t)}{r_i^2} & \frac{m_{ix}-x_t}{r_i^2} & \dots \end{bmatrix} \quad (17)$$

where (x_t, y_t) denote the robot's predicted position, (m_{ix}, m_{iy}) are the predicted coordinates of landmark i , and r_i is the expected range:

$$r_i = \sqrt{(m_{ix} - x_t)^2 + (m_{iy} - y_t)^2} \quad (18)$$

It is important to emphasize that $\mathbf{H}_{i,t}$ is sparse: its nonzero entries correspond only to the robot's pose components and the specific observed landmark i ; the other landmarks are unaffected in the measurement model. When multiple landmarks are observed

at once, the corresponding individual Jacobians $\mathbf{H}_{i,t}$ are stacked vertically to form the overall measurement Jacobian \mathbf{H}_t :

$$\mathbf{H}_t = \begin{bmatrix} \mathbf{H}_{1,t} \\ \mathbf{H}_{2,t} \\ \vdots \\ \mathbf{H}_{K,t} \end{bmatrix} \quad (19)$$

where K denotes the total number of observed landmarks at time t . Having computed Jacobian, the next step is to determine the innovation covariance \mathbf{S}_t , which represents the uncertainty associated with the difference between expected and actual observations:

$$\mathbf{S}_t = \mathbf{H}_t \boldsymbol{\Sigma}_{t|t-1} \mathbf{H}_t^T + \mathbf{R}_t^{eff} \quad (20)$$

Here, $R_{i,t}^{eff} = \frac{1}{\gamma_i} R_{i,t}$, $\gamma_i \in (0, 1]$. \mathbf{R}_t is the measurement noise covariance matrix, typically assumed known based on sensor characteristics. To preserve the statistical consistency of the EKF, entropy-based trust modulation is implemented as adaptive measurement noise inflation rather than direct innovation scaling. For each landmark i , the effective measurement covariance is defined by $R_{i,t}^{eff}$. The Kalman gain \mathbf{K}_t can now be computed, which balances trust between the predicted state and the new measurement.

It is given by:

$$\mathbf{K}_t = \boldsymbol{\Sigma}_{t|t-1} \mathbf{H}_t^T \mathbf{S}_t^{-1} \quad (21)$$

A larger Kalman gain indicates that the filter gives more weight to the measurement, while a smaller gain indicates more reliance on the prediction. With the Kalman gain available, the corrected mean $\boldsymbol{\mu}_t$ is obtained by adjusting the prior prediction by the innovation weighted by the Kalman gain:

$$\boldsymbol{\mu}_t = \boldsymbol{\mu}_{t|t-1} + \mathbf{K}_t \mathbf{r}_t \quad (22)$$

This update incorporates new information from the measurements to refine the state estimate. Simultaneously, the corrected covariance $\boldsymbol{\Sigma}_t$ is updated to reflect the reduced uncertainty after incorporating the measurement:

$$\boldsymbol{\Sigma}_t = (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \boldsymbol{\Sigma}_{t|t-1} \quad (23)$$

This ensures that the updated uncertainty is properly reduced based on the reliability of the measurements. To summarize the entire EKF-SLAM framework, at each time step, the filter proceeds through the following steps:

1. Prediction Step:
 - Predict the new state mean $\boldsymbol{\mu}_{t|t-1}$ using the motion model $g(\mathbf{x}, \mathbf{u})$,
 - Predict the new covariance $\boldsymbol{\Sigma}_{t|t-1}$ using the linearized motion model Jacobian \mathbf{G}_t .
2. Correction Step:
 - Use the sensor model to compute the expected measurement $\hat{\mathbf{z}}_t$,
 - Compute the innovation $\mathbf{r}_t = \mathbf{z}_t - \hat{\mathbf{z}}_t$,
 - Compute the measurement Jacobian \mathbf{H}_t by linearizing the sensor model,
 - Calculate the innovation covariance \mathbf{S}_t ,
 - Compute the Kalman gain \mathbf{K}_t ,
 - Update the mean and covariance with the correction terms.

4. PROPOSED METHOD

We begin our development from the standard correction step in EKF-SLAM. The EKF update equations for the state mean $\boldsymbol{\mu}_t$ and covariance $\boldsymbol{\Sigma}_t$ after incorporating sensor observations are given by:

$$\begin{cases} \boldsymbol{\mu}_t = \boldsymbol{\mu}_{t|t-1} + \mathbf{K}_t \mathbf{r}_t \\ \boldsymbol{\Sigma}_t = (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \boldsymbol{\Sigma}_{t|t-1} \end{cases} \quad (24)$$

Here, $\boldsymbol{\mu}_{t|t-1}$ is the predicted state mean, and $\boldsymbol{\Sigma}_{t|t-1}$ is the predicted covariance. The matrix \mathbf{H}_t is the Jacobian of the observation model with respect to the state, and \mathbf{K}_t is the Kalman gain computed as:

$$\mathbf{K}_t = \boldsymbol{\Sigma}_{t|t-1} \mathbf{H}_t^T (\mathbf{H}_t \boldsymbol{\Sigma}_{t|t-1} \mathbf{H}_t^T + \mathbf{R}_t)^{-1} \quad (25)$$

The term $\mathbf{r}_t = \mathbf{z}_t - \hat{\mathbf{z}}_t$ is the innovation or measurement residual, where \mathbf{z}_t is the actual observation, and $\hat{\mathbf{z}}_t = h(\boldsymbol{\mu}_{t|t-1})$ is the predicted observation based on the observation function $h(\cdot)$.

The core novelty of the proposed method lies in modulating the influence of each landmark observation according to its long-term reliability. Instead of directly scaling the innovation, which could lead to statistical inconsistency, we adjust the effective measurement uncertainty associated with each landmark. Specifically, a trust coefficient $\gamma_i \in (0, 1]$, computed from the temporal entropy of past innovations, is used to inflate the measurement noise covariance: $R_{i,t}^{eff} = \frac{1}{\gamma_i} R_{i,t}$, $\gamma_i \in (0, 1]$, where smaller trust values correspond to larger assumed measurement uncertainty. The innovation remains defined in the standard EKF form.

$$\mathbf{r}_t^i = (\mathbf{z}_t^i - \hat{\mathbf{z}}_t^i) \quad (26)$$

Its impact on the state update is naturally reduced through the Kalman gain computed using the inflated covariance. γ_i represents the normalized information content of the observation, and it dynamically adapts based on the entropy history of the corresponding landmark. When a landmark is observed for the first time, no observation history is available to compute a reliable entropy estimate. To address this cold-start situation, the trust coefficient is initialized progressively according to the number of observations accumulated for that landmark. Specifically, the trust value increases gradually from a conservative initial level and reaches full entropy-based evaluation once a minimum history length is obtained. This prevents newly initialized landmarks—whose positions are still highly uncertain—from exerting excessive influence on the state update, while ensuring that they are not permanently suppressed. After sufficient observations are collected, the standard entropy-based trust modulation is applied. We compute the rolling entropy of the measurement stream for landmark i over a recent time window. Let $\mathcal{Z}_i = \{\mathbf{z}_{t-k}^i, \dots, \mathbf{z}_t^i\}$ denote the sequence of past range-bearing observations to landmark i . We construct a histogram of these measurements over pre-defined bins to estimate the empirical probability distribution $P_i = \{p_1, p_2, \dots, p_n\}$. The Shannon entropy is then calculated as:

$$H(\mathcal{Z}_i) = - \sum_{j=1}^n p_j \log(p_j + \epsilon) \quad (27)$$

where ϵ is a small positive constant added for numerical stability.

The entropy estimation depends on two parameters: the rolling window length k and the number of histogram bins n . The window length controls the trade-off between responsiveness and statistical stability. In practice, k is chosen to include sufficient samples for reliable distribution estimation (typically 10–20 observations per

landmark). The number of bins is determined using the Freedman–Diaconis rule to balance resolution and sampling noise. Sensitivity analysis showed that moderate variations of these parameters affect only the smoothness of trust adaptation while preserving the relative performance trends of the proposed method.

Although raw range and bearing measurements naturally vary as the robot moves, such deterministic geometric changes remain structured and consistent with the motion and observation models. Over a short temporal window, these variations produce a concentrated empirical distribution. In contrast, unreliable observations arising from occlusion, aliasing, or sensing disturbances lead to irregular fluctuations that broaden the distribution and increase entropy. Therefore, the entropy measure primarily captures temporal observation consistency rather than deterministic motion-induced variation.

The size of the rolling entropy window W governs the trade-off between responsiveness and stability of the trust coefficient γ_i . A shorter window allows the entropy estimate to react quickly to sudden changes in landmark observability (e.g., temporary occlusion or sensor degradation), resulting in faster trust adaptation. However, this may introduce higher variance and sensitivity to transient noise. Conversely, a longer window smooths short-term fluctuations and provides a more stable estimate of landmark reliability, at the cost of slower adaptation to abrupt environmental changes. In our implementation, W was chosen to balance these effects, ensuring both temporal stability and reactivity.

The entropy estimation relies on histogram binning of recent measurements. The number of bins n was selected to provide sufficient resolution while maintaining statistical stability, avoiding over-fragmentation of sparse data. A moderate bin count ensures that entropy reflects genuine measurement variability rather than discretization artifacts. Empirically, we found that results are robust to moderate variations in n , provided that bins adequately cover the measurement range. To normalize the entropy into the interval $[0,1]$, we divide it by the maximum possible entropy $H_{\max} = \log(n)$, yielding the trust weight:

$$\gamma_i = \frac{H_{\max} - H(\mathcal{Z}_i)}{H_{\max}} \quad (28)$$

This means that landmarks with low entropy (i.e., consistent and reliable observations) are assigned $\gamma_i \approx 1$, while those with highly uncertain or noisy measurements receive $\gamma_i \approx 0$.

Let K denote the number of landmarks observed at time t . We stack all residuals \mathbf{r}_t^i to form the total innovation vector \mathbf{r}_t , and organize the γ_i values into a block-diagonal matrix:

$$\Gamma_t = \text{diag}(\gamma_1 \mathbf{I}_2, \gamma_2 \mathbf{I}_2, \dots, \gamma_K \mathbf{I}_2) \quad (29)$$

Here, each \mathbf{I}_2 corresponds to the dimensionality (e.g., range and bearing) of a single landmark measurement. We then define the entropy-aware residual vector as:

$$\mathbf{r}_t = \Gamma_t (\mathbf{z}_t - \hat{\mathbf{z}}_t) \quad (30)$$

The Kalman gain and the Jacobian remain unchanged and are computed as in standard EKF-SLAM, but the measurement residual now carries an embedded notion of temporal feature trustworthiness.

This entropy-aware innovation scaling introduces several key advantages:

- **Dynamic Observation Trust:** Unlike static measurement noise models, this method modulates measurement influence based on observation history.

- **Long-Term Feature Assessment:** Landmarks that repeatedly provide ambiguous or noisy data are automatically de-emphasized over time.
- **Robustness to Aliasing and Outliers:** By reducing the contribution of perceptually aliased or unstable landmarks, the filter becomes less sensitive to false updates.
- **Filter Compatibility:** The mechanism integrates seamlessly into the EKF structure without modifying the motion model or requiring additional learning components.

Thus, the proposed EFG-EKF-SLAM framework improves estimation robustness by embedding information-theoretic observability directly into the filtering process, leveraging entropy as a dynamic, interpretable, and computationally efficient confidence measure. The computational overhead of the proposed entropy-gated mechanism is minimal. For each observed landmark, the method requires only a histogram update and a scalar entropy computation over a fixed window. These operations scale linearly with the number of observations per landmark and do not alter the matrix dimensions involved in the EKF update. Consequently, the runtime complexity remains dominated by the EKF covariance update, preserving real-time feasibility comparable to standard EKF-SLAM. At the beginning of the mission, when insufficient measurement history is available, each new landmark is assigned a neutral trust value $\gamma_i = 1$. As more observations accumulate, the entropy profile gradually refines this trust estimate. This ensures stable early behavior without prematurely suppressing new features. The step-by-step implementation of the proposed entropy-gated innovation mechanism within the EKF-SLAM correction stage is outlined in Algorithm 1 for clarity and reproducibility.

Algorithm 1. Entropy-Gated EKF-SLAM Correction.

For each observed landmark i :

- Append current measurement to rolling window \mathcal{Z}_i
 - Update histogram and compute entropy $H(\mathcal{Z}_i)$
 - Normalize entropy to obtain trust γ_i
 - Compute effective measurement noise $\mathbf{R}_{i,t}^{\text{eff}}$
- Stack residuals and apply standard EKF update.

5. EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed Entropy-Gated Feature-aware EKF-SLAM (EFG-EKF-SLAM) framework compared to the classical EKF-SLAM, four experimental scenarios were designed, each representing different real-world challenges. The robot motion and observation models were kept consistent across all experiments, while environmental conditions such as measurement noise and landmark distribution were varied to simulate different complexities. For each scenario, both EKF-SLAM and EFG-EKF-SLAM algorithms were run in parallel. For each case, a figure comprising four subplots is presented: robot trajectory comparison (top-left), landmark mapping and confidence ellipses (top-right), entropy dynamics (bottom-left), and pose estimation error over time (bottom-right). The motion noise covariance was set to $Q_t = \text{diag}(0.02^2, 0.02^2, 0.01^2)$, and the nominal measurement noise covariance was $R_t = \text{diag}(0.1^2, (2^\circ)^2)$. In noisy scenarios, measurement noise variance was increased up to threefold to simulate degraded sensing conditions. The experiments are detailed below, and a quantitative comparison across all cases is summarized in Table 2.

5.1. Case 1: Clean Environment

In the first experiment displayed in Fig. 1, landmarks were sparsely distributed with low measurement noise. As expected, both EKF-SLAM and EFG-EKF-SLAM performed comparably well. Robot trajectories almost overlapped, and landmark estimations were accurate for both methods. The entropy dynamics remained stable and high, indicating consistent, trustworthy observations. Pose error was low for both approaches. In this scenario, EFG-EKF-SLAM showed marginal improvements in map compactness and pose stability due to its adaptive weighting but was not critical because of the ideal sensing conditions.

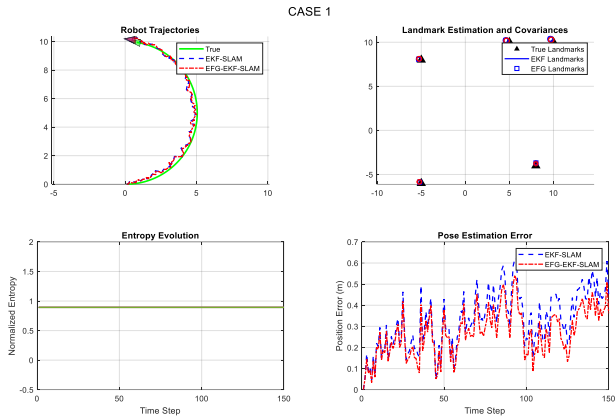


Fig. 1. Case 1: Clean Environment

5.2. Case 2: Noisy Environment

The second experiment (Fig. 2) introduced higher measurement noise, simulating sensor uncertainty or environmental interference. EKF-SLAM began to accumulate notable trajectory drift and produced broader confidence ellipses around landmarks. EFG-EKF-SLAM, by dynamically adjusting the Kalman update using per-landmark entropy, maintained a more accurate trajectory and smaller landmark uncertainties. Entropy profiles revealed the system's ability to detect unreliable measurements. The pose error plot demonstrated that EFG-EKF-SLAM consistently outperformed EKF-SLAM throughout the mission. This experiment highlighted the significance of adaptive trust mechanisms under high-noise conditions.

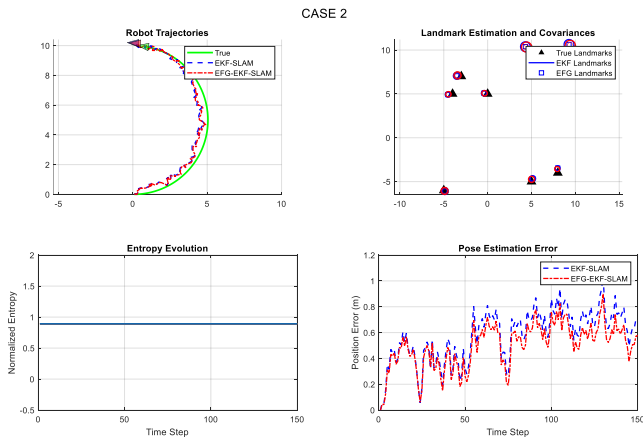


Fig. 2. Case 2: Noisy Environment

5.3. Case 3: Aliasing Environment

In the third experiment displayed in Fig. 3, landmarks were placed closely together to induce perceptual aliasing. Here, EKF-SLAM suffered significantly from incorrect data association, causing distorted maps and large uncertainties. EFG-EKF-SLAM leveraged its entropy-based innovation gating to detect ambiguous landmark observations. Consequently, it reduced the influence of unstable measurements and maintained a cleaner map. Although some errors remained due to extreme aliasing, EFG-EKF-SLAM managed to suppress the most damaging updates. Entropy traces in this scenario fluctuated more sharply, correctly reflecting observation inconsistencies.

5.4. Case 4: Dynamic Noise Environment

The fourth experiment (Fig. 4) modeled real-world sensor degradation by alternating between low and high measurement noise every 30 timesteps. EKF-SLAM, assuming constant noise, was unable to adapt, resulting in severe trajectory drift during noisy periods. In contrast, EFG-EKF-SLAM detected noise level changes through entropy variations and dynamically down-weighted bad measurements. This resulted in significantly improved trajectory tracking and better landmark estimations. The entropy plots showed cyclic patterns, decreasing during noisy phases and recovering during clean phases, illustrating the adaptive behavior of EFG-EKF-SLAM.

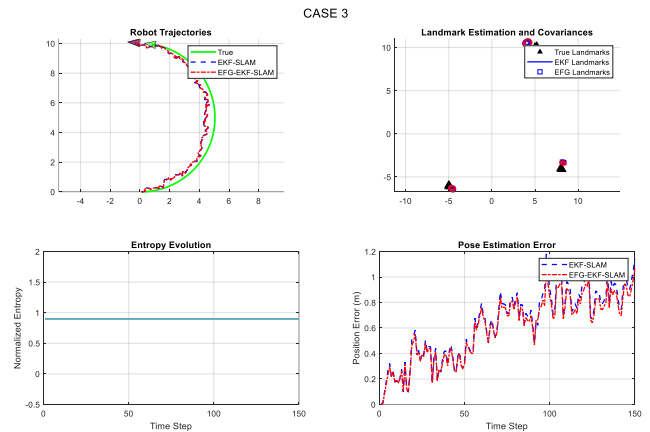


Fig. 3. Case 3: Aliasing Environment

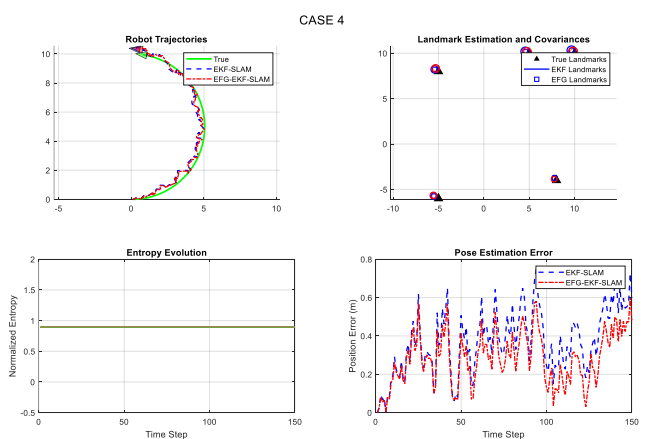


Fig. 4. Case 4: Dynamic Noise

5.5. Comparative Summary

The overall comparative performance of EKF-SLAM and EFG-EKF-SLAM across the four scenarios is summarized in Table 2. As can be seen, while both methods perform similarly under ideal conditions, EFG-EKF-SLAM exhibits substantial advantages in noisy, ambiguous, and dynamic environments by actively managing trust through historical entropy profiles. Although EKF-SLAM has quadratic covariance scaling with the number of landmarks, the proposed trust matrix Γ_t is block-diagonal with small fixed blocks and does not alter state dimensionality or covariance structure. Therefore, memory requirements remain unchanged relative to standard EKF-SLAM. Future work will evaluate the method on real-world SLAM datasets to further validate applicability beyond simulation. Moreover, in environments where only a small number of landmarks are visible, the proposed method remains stable because entropy is computed independently per landmark. When observations are sparse but consistent, entropy remains low and trust coefficients stay high, ensuring that the filter does not unnecessarily suppress informative measurements. Thus, the approach gracefully degrades to standard EKF behavior in sparse but reliable settings.

Tab. 2. Summary of EKF-SLAM vs EFG-EKF-SLAM performance across experiments

Scenario	EKF-SLAM Behavior	EFG-EKF-SLAM Behavior	Main Observations
Clean Environment (Fig. 1)	Accurate pose and map	Accurate pose and map (slightly better)	Minimal difference, EFG marginally improves consistency
Noisy Environment (Fig. 2)	Drift, larger landmark uncertainty	Stable pose, smaller ellipses	EFG outperforms in noise suppression
Aliasing Environment (Fig. 3)	Map distortion, large uncertainties	Cleaner map, suppressed bad updates	EFG detects ambiguous landmarks
Dynamic Noise (Fig. 4)	Severe drift during noisy periods	Stable pose through adaptive trust	EFG dynamically reacts to sensor degradation

6. CONCLUSION


In this work, we introduced Entropy-Gated Feature-Aware EKF-SLAM (EFG-EKF-SLAM), an adaptive enhancement of the classical EKF-SLAM framework that incorporates information-theoretic trust modulation directly into the Kalman update. By monitoring the historical entropy profiles of landmark observations, our approach dynamically adjusts the influence of each measurement based on its long-term consistency, enabling the SLAM system to suppress ambiguous or unreliable features without requiring external classifiers or additional sensing modalities. Extensive simulations across four distinct scenarios — clean environments, high-noise sensing, perceptual aliasing, and dynamically changing noise conditions — confirmed the effectiveness of the proposed method. Compared to standard EKF-SLAM, EFG-EKF-SLAM consistently demonstrated improved trajectory accuracy, reduced landmark uncertainty, and increased resilience against both measurement noise and perceptual ambiguity. In particular, the entropy-adaptive gating

mechanism proved crucial in environments characterized by non-stationary sensor reliability and spatial aliasing, where traditional static noise assumptions fail to maintain map fidelity. Moreover, EFG-EKF-SLAM maintains the lightweight computational footprint inherent to EKF architectures, ensuring real-time applicability for resource-constrained robotic platforms. Overall, the results validate that embedding long-term observability cues into the filtering process substantially enhances SLAM robustness, offering a promising pathway for next-generation autonomous navigation systems operating in uncertain and dynamic environments. While the proposed EFG-EKF-SLAM framework introduces an effective information-theoretic mechanism to modulate measurement influence based on entropy, further extensions could improve adaptability in more complex or non-Gaussian environments. For instance, future work could explore incorporating intelligent clustering algorithms similar to those used in radar detection under k -distributed sea clutter [25], enabling the SLAM system to dynamically group and reclassify landmarks based on uncertainty structure or spatial ambiguity. Such clustering could help disambiguate features in environments with dense or repeating visual patterns. Additionally, methods inspired by deep learning-based signal estimation [26][27] could be leveraged to enhance landmark observability under perceptual noise. Specifically, neural networks trained to mitigate environmental clutter or to denoise weak signals may be adapted to improve feature detection confidence before entropy computation. These strategies may enable EFG-EKF-SLAM to better handle sensor drift, occlusions, or poor lighting conditions by learning contextual patterns beyond purely geometric cues. Integrating such techniques would allow the filter to operate more robustly in real-world, perceptually challenging scenarios, further strengthening the system's reliability and extending its applicability to autonomous navigation in degraded sensing conditions.

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