



Research Article

Analysis of Information Degradation and Reliability Transitions via Structured Noise Injection in Multisensor Localization

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ABSTRACT

This study investigates information degradation and reliability transitions in multisensor localization systems using a structured noise injection approach. A five-sensor localization scenario is considered, where range measurements are intentionally corrupted by Gaussian perturbations, intermittent burst disturbances, and positive measurement biases. Target coordinates are estimated using a weighted nonlinear least-squares method, while localization performance is evaluated through root mean square error (RMSE), Fisher Information Matrix (FIM), Cramér–Rao Lower Bound (CRLB), and failure rate metrics. Experiments are conducted under signal-to-noise ratio (SNR) levels ranging from -5 dB to 25 dB using 600 Monte Carlo realizations for each operating condition. The results show that increasing perturbation levels progressively reduce localization accuracy and information content while increasing theoretical uncertainty. A distinct reliability transition region is observed between 5 dB and 10 dB, where localization failures rapidly decrease as measurement quality improves. The findings demonstrate that controlled noise injection provides a practical means of exposing information-deficient operating conditions and reliability boundaries in multisensor localization systems.

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Introduction

Although information theory is often associated with communication capacity, its broader perspective concerns how uncertainty is reduced through imperfect observations [1], [2]. In localization problems, this perspective appears naturally in estimation-theoretic quantities such as the Fisher Information Matrix (FIM) and the Cramér–Rao Lower Bound (CRLB), which characterize how measurement quality translates into positional certainty.

Multisensor localization plays a central role in wireless sensing, surveillance, navigation, and target tracking applications, where the position of a target must be inferred from measurements collected by spatially separated sensors [3], [4], [5], [6], [7], [8], [9], [10]. Among the available localization paradigms, range-based methods remain widely used because the geometric relationship between sensor locations and target coordinates can be expressed directly and solved with relatively simple estimation procedures [11], [12]. In such systems, localization performance depends not only on the estimator itself but also on sensor geometry, measurement quality, and the statistical structure of the observation errors [13], [14].

A substantial body of research has examined localization from the perspectives of estimation accuracy and theoretical performance limits. Least-squares and weighted least-squares formulations are commonly adopted in range-based localization because they provide practical solutions for nonlinear position estimation problems [15], [16], [17], [18]. At the same time, the FIM [19], [20] and the CRLB [21], [22], [23] have been widely used to quantify the information content of measurements and the minimum achievable uncertainty under given sensing conditions. This literature has shown that localization accuracy is closely tied to the amount of available information and to the geometric diversity of the sensing configuration.

In practice, however, measurement degradation is rarely limited to ideal zero-mean Gaussian noise. Real sensing environments often involve intermittent disturbances, non-line-of-sight effects, burst-like corruption, calibration mismatch, and positive ranging biases, all of which may distort the observation model and produce large localization errors [24], [25], [26]. For this reason, many studies focus on localization methods that reject outliers, mitigate non-line-of-sight bias, or jointly estimate nuisance error components together with the target position [27], [28]. These works have demonstrated that localization systems

may exhibit highly nonlinear degradation behaviour when measurement corruption becomes sufficiently severe.

Recent experimental studies provide direct evidence that propagation and link conditions can produce non-Gaussian and time-varying measurement errors. UWB experiments show that NLoS propagation and multipath interference increase ranging bias and reduce positioning accuracy, while channel-quality information can be used to distinguish LoS, soft-NLoS, hard-NLoS, and multipath links [29], [30]. Field tests conducted in indoor construction environments further report error growth under human shadowing, wall obstruction, anchor handover, and unfavourable anchor geometry [31]. Experimental Wi-Fi backscatter results also indicate that LoS/NLoS propagation, residual interference, antenna-dependent gain variation, and link-quality constraints alter the feasible operating region of networked IoT systems [32]. These observations support the use of intermittent burst disturbances and positive range biases as simplified representations of practical sensing degradation.

Despite this progress, much of the existing literature is centred either on improving localization algorithms under corrupted measurements or on deriving theoretical bounds under fixed modelling assumptions [12], [13], [28]. Comparatively fewer studies investigate how controlled perturbation mechanisms can be used as an analysis tool to reveal the transition from reliable localization to failure-prone operation. This question is important because average accuracy metrics alone may not fully capture the onset of instability, whereas reliability-oriented analyses suggest that localization systems can undergo abrupt operational changes as measurement quality deteriorates [33].

Motivated by this gap, the present study investigates information degradation and reliability transitions in multisensor localization through a structured noise injection framework. A five-sensor range-based localization scenario is considered in which Gaussian perturbations, intermittent burst disturbances, and positive measurement biases are intentionally introduced into the acquired measurements while the sensor geometry and estimation procedure are kept fixed. This design makes it possible to isolate the effect of measurement degradation from changes in sensor placement or algorithmic structure. Target coordinates are estimated using a weighted nonlinear least-squares approach, and localization behaviour is evaluated by combining empirical performance measures, such as root mean square error (RMSE) and failure rate, with information-theoretic indicators derived from the FIM and CRLB.

The novelty of this study lies in the use of structured noise injection as an information probe rather than as a test condition for a newly proposed estimator. Existing localization studies generally concentrate on reducing estimation error, suppressing outliers, compensating for non-line-of-sight bias, or deriving theoretical bounds under fixed error assumptions. Here, the sensor geometry and weighted nonlinear least-squares estimator remain unchanged, while Gaussian perturbations, intermittent burst

events, and positive range biases are varied in a controlled manner. RMSE, failure rate, FIM, and CRLB are then evaluated together to reveal how information loss, uncertainty growth, and operational failure develop across the same SNR range. The focused 5–10 dB analysis further identifies a narrow interval in which reliability changes rapidly despite the unchanged estimator structure.

Although the present study is limited to a fixed five-sensor, two-dimensional scenario with a stationary target, the proposed framework can be extended in several directions. Future work may consider dynamic targets, time-varying sensor geometry, larger multisensor networks, and three-dimensional localization settings. It would also be valuable to investigate additional perturbation models, such as correlated noise, missing measurements, synchronization mismatch, and non-line-of-sight propagation, as well as to compare the observed reliability transitions across alternative estimators and adaptive sensor fusion strategies.

The remainder of this paper is organized as follows. Section 2 presents the material and method, including the multisensor localization model, sensor geometry, weighted nonlinear least-squares estimation framework, structured noise injection model, and information-theoretic analysis. Section 3 reports the findings and discussion by examining localization error, information degradation, and reliability transition behavior under different signal-to-noise ratio conditions. Finally, Section 4 concludes the paper.

Material and Method

System Model

This section describes the multisensor localization scenario considered throughout the study. A five-sensor network is deployed over a two-dimensional surveillance region, where each sensor independently acquires range measurements from a stationary target. The localization process relies on geometric information extracted from multiple observations rather than on a centralized sensing structure. The selected configuration allows the influence of measurement perturbations to be examined under a controlled and repeatable setting while preserving the spatial diversity commonly encountered in distributed sensing applications. Sensor positions remain fixed during all experiments, and target coordinates are estimated from noisy range observations using a nonlinear least-squares formulation.

Sensor Geometry

A multisensor localization scenario consisting of five spatially separated sensors is considered. The sensors are deployed over a two-dimensional region according to the coordinates listed in Table 1. Four sensors are positioned near the corners of the monitored area, while an additional sensor is placed closer to the centre. This arrangement introduces geometric diversity and allows target observations to be collected from multiple directions.

Table 1. Coordinates of the sensor network.

Sensor	x (km)	y (km)
S1	0	0
S2	10	0
S3	0	10
S4	10	10
S5	5	0.5
Target	5	5

A stationary target is located at $(x, y) = (5, 5)$ km. Figure 1 illustrates the sensor deployment together with the equal-range circles corresponding to the true target position. Under ideal measurement conditions, the circles intersect at a common point representing the target location. As measurement perturbations increase, the intersection region becomes progressively distorted, leading to localization uncertainty and estimation errors.

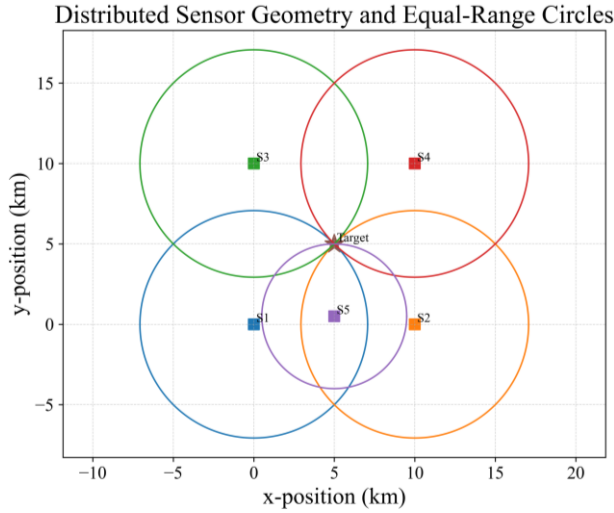


Figure 1. Five-sensor localization geometry and equal-range circles.

The selected geometry is intentionally kept fixed throughout all experiments. Variations in localization accuracy, information metrics, and failure statistics then reflect measurement degradation under the fixed sensor geometry. This assumption enables the effects of structured noise injection to be examined independently of geometric reconfiguration.

Measurement Model

Each sensor acquires an independent range measurement with respect to the target position. Let (x, y) denote the unknown target coordinates and (x_i, y_i) represent the location of the i -th sensor. The true geometric distance between the target and sensor i is expressed as,

$$d_i = \sqrt{[(x - x_i)^2 + (y - y_i)^2]} \quad (1)$$

where d_i denotes the Euclidean range. The localization process utilizes the set of distances collected from all available sensors to estimate the target position.

In the absence of measurement perturbations, the range observations correspond exactly to the geometric distances defined by (1). Under such conditions, the equal-range circles generated by multiple sensors intersect at the true target location. Practical sensing environments, however, introduce deviations from the ideal ranges. These perturbations modify the intersection structure of the circles and consequently affect localization accuracy. The measurement corruption mechanisms considered in this study are introduced in Section 2.2.

Weighted Nonlinear Least-Squares Localization

The target position is estimated from the range measurements collected by the sensor network. Since the measurement model in (1) is nonlinear with respect to the target coordinates, a weighted nonlinear least-squares (NLS) formulation is adopted. Let r_i denote the measured range associated with sensor i , while $\hat{d}_i$ represents the predicted distance obtained from a candidate target position. The localization problem is formulated as,

$$J(\hat{\mathbf{p}}) = \sum_{i=1}^M \left(\frac{r_i - \hat{d}_i}{\sigma_i} \right)^2 \quad (2)$$

where M denotes the number of sensors, $\hat{\mathbf{p}} = [\hat{x}, \hat{y}]^T$ is the estimated target position, and σ_i represents the measurement uncertainty associated with sensor i . The weighting term allows measurements with different noise characteristics to contribute proportionally to the estimation process. The weighting coefficients are derived from the nominal sensor uncertainty values. Burst and bias corruption events are not assumed to be known by the estimator during individual Monte Carlo realizations. The estimator therefore operates under model mismatch: intermittent burst events and positive biases are present, but neither component is compensated during optimization.

For each Monte Carlo realization, the weighted NLS problem is solved using all available sensor observations. The resulting position estimate is subsequently utilized to compute the localization error, reliability statistics, and information-theoretic metrics. The localization algorithm remains unchanged throughout all experiments. Since the same estimator is used in every realization, changes in the reported metrics arise from the injected measurement perturbations rather than from algorithmic variation.

Structured Noise Injection Model

The localization model described in Section 2 assumes that target coordinates are estimated from range observations collected by a sensor network. In practical sensing environments, measurements are rarely affected by a single noise source. Instead, sensing systems may experience a combination of random fluctuations, intermittent disturbances, and systematic biases originating from

environmental conditions, hardware limitations, or propagation effects. To investigate how such perturbations influence localization reliability and information content, a structured noise injection model is adopted. The proposed model introduces controlled measurement degradations with varying severity levels while preserving the underlying sensor geometry and estimation procedure. This approach allows the resulting changes in localization accuracy, Fisher information, and failure characteristics to be examined in a systematic manner.

Gaussian Measurement Perturbation

The first component of the proposed perturbation model consists of additive Gaussian measurement noise. Let d_i denote the true distance between the target and the i -th sensor. The corresponding range observation is expressed as,

$$r_i = d_i + n_i, \quad (3)$$

where n_i represents a zero-mean Gaussian random variable with variance σ_i^2 ,

$$n_i \sim \mathcal{N}(0, \sigma_i^2). \quad (4)$$

The variance level is adjusted according to the selected signal-to-noise ratio (SNR) condition. Sensor-dependent scaling factors are incorporated to emulate heterogeneous sensing quality across the sensor network. The measurement uncertainty therefore differs among sensors even under the same SNR condition. The Gaussian term defines the baseline error level. Burst and bias components are added separately in Sections 2.2.2 and 2.2.3.

Intermittent Burst Corruption

In practical sensing systems, measurement degradation is not always limited to stationary Gaussian noise. Communication interruptions, temporary interference sources, synchronization errors, and environmental disturbances may occasionally produce measurement deviations that are significantly larger than the nominal noise level. To emulate such effects, an intermittent burst corruption mechanism is incorporated into the perturbation model.

For each sensor observation, a burst event is generated according to a probability p_b . When a burst event occurs, an additional high-variance perturbation is introduced into the corresponding range measurement. The corrupted observation can be expressed as,

$$r_i = d_i + n_i + b_i, \quad (5)$$

where n_i denotes the Gaussian perturbation introduced in Section 2.2.1 and b_i represents the burst corruption term. The burst component is modelled as,

$$b_i = \begin{cases} \mathcal{N}(0, \alpha^2 \sigma_i^2), & \text{with probability } p_b \\ 0, & \text{otherwise} \end{cases}, \quad (6)$$

where α is a scaling factor that controls the burst severity and σ_i denotes the nominal measurement uncertainty of sensor i . To reflect the increased likelihood of measurement corruption under unfavourable operating conditions, the burst probability is adapted according to the SNR level. Low-SNR scenarios experience a larger number of burst events, whereas high-SNR conditions are affected less frequently. This mechanism introduces intermittent and nonstationary measurement degradation, enabling the transition from stable localization behaviour to failure-prone operating regimes to be examined.

Positive Bias Corruption

In addition to random fluctuations and burst disturbances, practical sensing systems may occasionally exhibit systematic measurement shifts. Such deviations may originate from propagation delays, non-line-of-sight conditions, calibration inaccuracies, or hardware imperfections. To represent these effects, a positive bias corruption component is incorporated into the perturbation model. The range observation is modified as in (7),

$$r_i = d_i + n_i + b_i + c_i, \quad (7)$$

where c_i denotes the bias component. Unlike Gaussian and burst perturbations, the bias term introduces a directional shift that consistently increases the measured distance. A bias event occurs with probability p_c , while no additional offset is applied otherwise. The probability of bias occurrence is adjusted according to the operating SNR condition. Thus, adverse sensing environments are characterized by a higher likelihood of biased observations. The positive offset is evaluated together with the Gaussian and burst components.

Noise-Model Parameters and Failure Criterion

The parameters of the structured noise model are kept fixed throughout the experiments. The Gaussian range-noise standard deviation is computed as $0.25/10^{\text{SNR}/20}$ km. Sensor-dependent measurement uncertainty is introduced by multiplying this value by [1.00, 1.15, 0.95, 1.25, 0.85] for sensors S_1 – S_5 , respectively.

The probability of a burst event is defined as,

$$0.03 + \frac{0.32}{1 + \exp((\text{SNR} - 6)/3)} \quad (8)$$

When a burst event occurs, an additional zero-mean Gaussian perturbation with a standard deviation equal to four times the nominal sensor uncertainty is added to the corresponding range measurement. The probability of a positive bias event is defined as,

$$0.02 + \frac{0.20}{1 + \exp((\text{SNR} - 4)/3.5)} \quad (9)$$

For an active bias event, the positive offset is sampled from an exponential distribution. Its scale parameter is equal to

the SNR-dependent Gaussian standard deviation. A Monte Carlo realization is classified as a localization failure when the Euclidean position error exceeds 200 m. Each SNR condition is evaluated using 600 Monte Carlo realizations, and the random-number generator is initialized with seed 7. These settings are applied without modification in both the original SNR sweep and the focused 5–10 dB analysis.

Information-Theoretic Analysis

The structured perturbation model described in Section 2.2 alters the quality of the acquired range measurements and affects the localization process. To quantify these effects, several information-theoretic and performance-based metrics are employed. The analysis focuses on three complementary aspects: the amount of information available for localization, the theoretical lower bound of estimation uncertainty, and the operational reliability of the localization system. The analysis uses the FIM, CRLB trace, RMSE, and failure rate to examine these changes from complementary perspectives.

Fisher Information Matrix

The Fisher Information Matrix (FIM) is employed to quantify the amount of localization information contained in the sensor measurements. For range-based localization systems, the FIM characterizes the sensitivity of the observations to variations in the target coordinates. Higher information levels correspond to improved localization capability, whereas lower information levels indicate increased uncertainty and ambiguity in the estimation process. The FIM is defined as,

$$F = H^T R^{-1} H, \quad (10)$$

where H denotes the Jacobian matrix of the range measurement model and R represents the measurement covariance matrix. The Jacobian matrix contains the partial derivatives of the sensor observations with respect to the target coordinates, while the covariance matrix describes the uncertainty associated with the range measurements.

In this study, the FIM is evaluated under different perturbation conditions to investigate how structured noise injection influences the amount of information available for localization. The logarithm of the determinant of the FIM is utilized as a compact indicator of information content, where larger values correspond to increased localization information.

Cramér–Rao Lower Bound

The Cramér–Rao Lower Bound (CRLB) provides the theoretical lower bound on the covariance of any unbiased estimator. For localization problems, the CRLB is directly related to the FIM and quantifies the minimum achievable estimation uncertainty under a given measurement condition. The CRLB is obtained as,

$$CRLB = F^{-1}, \quad (11)$$

where F denotes the Fisher Information Matrix defined in (10). Smaller CRLB values indicate lower theoretical uncertainty and improved localization capability, whereas larger values correspond to increased estimation ambiguity.

Here, the trace of the CRLB matrix is utilized as a scalar indicator of localization uncertainty. This metric enables the effects of structured perturbations on the theoretical estimation limit to be examined across different operating conditions. The reported CRLB values should be interpreted as theoretical uncertainty bounds under the assumed local covariance model. Since the perturbation model additionally includes burst and bias corruption mechanisms, practical localization errors may deviate from the ideal bound under severe degradation conditions. The reported CRLB is not treated as a strict lower bound for the complete burst- and bias-corrupted measurement model; it is used as a nominal uncertainty indicator derived from the adopted effective covariance representation.

Findings and Discussion

The proposed model is evaluated using the multisensor localization scenario defined in Section 2. A stationary target is positioned at the centre of the surveillance region, while range measurements are acquired from all sensors and processed using the weighted nonlinear least-squares estimator. Structured perturbations consisting of Gaussian noise, intermittent burst corruption, and positive bias corruption are injected into the measurements according to the procedure described in Section 2.2.

The experiments are conducted under SNR levels ranging from –5 dB to 25 dB. For each operating condition, 600 Monte Carlo realizations are performed to generate statistically meaningful performance estimates. Localization accuracy, information degradation, and reliability characteristics are evaluated using RMSE, FIM, CRLB, and failure rate metrics. The obtained results are discussed in terms of localization performance, information content, and operational reliability.

RMSE Behaviour

The localization accuracy of the proposed approach is evaluated under SNR conditions ranging from –5 dB to 25 dB. The corresponding performance metrics are summarized in

Table 2, while the RMSE behaviour is illustrated in Figure 2.

As expected, localization accuracy improves as the measurement quality increases. The RMSE decreases from 1094.8 m at –5 dB to 16.8 m at 25 dB, indicating a substantial reduction in estimation error under favourable sensing conditions. However, the degradation trend is not linear across the investigated SNR range. The most significant improvement is observed between 5 dB and 10 dB, where the RMSE decreases from 285.6 m to 128.3 m.

Table 2. Localization and information-theoretic performance under different SNR conditions.

SNR (dB)	RMSE (m)	Median Error (m)	P90 Error (m)	Failure Rate	log det(FIM)	trace(CRLB) (m ²)
-5	1094.789	735.972	1773.862	0.9500	1.1455	1176337.633
0	627.060	439.088	1034.289	0.8117	3.6092	343216.476
5	285.620	187.589	469.440	0.4650	6.5101	80483.497
10	128.319	79.615	200.775	0.1050	9.9413	14477.397
15	56.104	39.662	82.765	0.0000	13.0334	3085.197
20	29.326	21.939	43.660	0.0000	15.5804	863.467
25	16.765	11.634	24.629	0.0000	17.9355	265.977

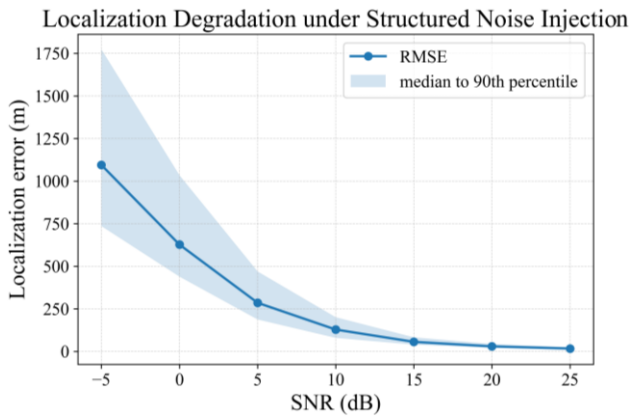


Figure 2. RMSE variation under different SNR conditions.

A similar behaviour is observed in the error distribution statistics. The 90th percentile error decreases from 1773.9 m at -5 dB to 24.6 m at 25 dB, demonstrating that high-error localization events become considerably less frequent as the perturbation level decreases. These results indicate that structured noise injection not only affects the average localization performance but also influences the occurrence of large estimation deviations.

The results show that localization degradation becomes increasingly pronounced under low-SNR conditions. The nonlinear reduction of both RMSE and percentile-based error metrics suggests the presence of a transition region in which small improvements in measurement quality lead to substantial gains in localization performance.

Information Degradation Analysis

The information degradation characteristics of the proposed model are evaluated using the logarithm of the determinant of the FIM and the trace of the CRLB. The corresponding results are illustrated in Figure 3 and Figure 4.

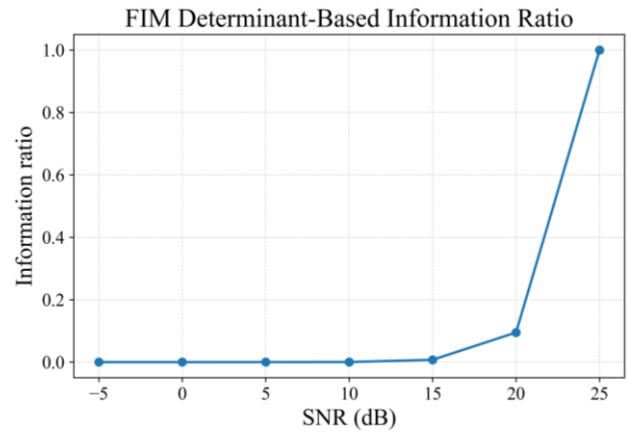


Figure 3. Variation of log-det(FIM) with SNR.

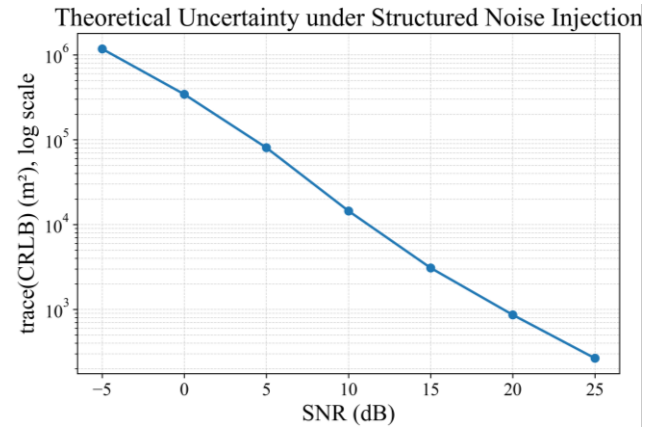


Figure 4. Localization uncertainty quantified by trace(CRLB).

As shown in Figure 3, the amount of localization information increases consistently with increasing SNR. The log-det(FIM) metric rises from 1.15 at -5 dB to 17.94 at 25 dB, indicating a substantial improvement in the observability of the target position. This behaviour confirms that structured perturbations progressively reduce the information content available for localization under adverse operating conditions.

The information ratio shown in Figure 3 is obtained by normalizing the logarithmic determinant of the FIM with respect to the maximum information level observed at 25 dB. Values close to unity indicate operating conditions with

information content approaching the highest-information reference scenario.

The CRLB results presented in Figure 4 exhibit an inverse trend. The $\text{trace}(\text{CRLB})$ decreases significantly as the measurement quality improves, demonstrating a reduction in theoretical estimation uncertainty. At low SNR levels, severe perturbations lead to large uncertainty bounds, whereas high-SNR conditions provide substantially tighter localization limits.

A clear consistency is observed between the information-theoretic metrics and the localization performance results presented in Section 3.1. As the Fisher information increases, the theoretical uncertainty decreases, and the localization error is correspondingly reduced. Across the tested SNR range, lower Fisher information is accompanied by a higher CRLB trace and larger localization error.

Reliability Transition

The operational reliability of the localization system is investigated using the failure rate metric and the distribution of localization errors. The corresponding results are presented in Figure 5 and Figure 6.

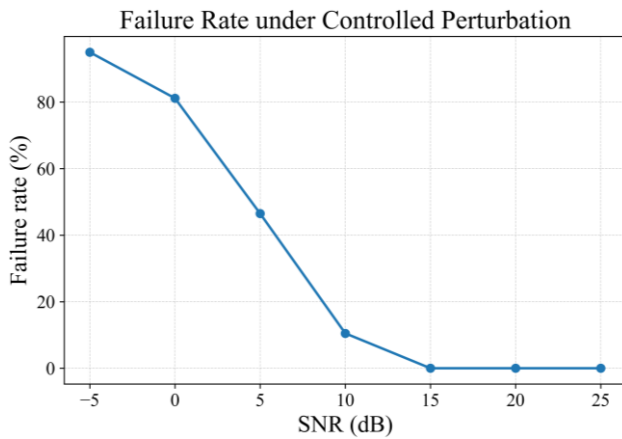


Figure 5. Localization failure rate under structured perturbations.

Figure 5 demonstrates a pronounced reliability transition as the perturbation level decreases. At low SNR conditions, the localization system experiences a large number of failed estimations. The failure rate reaches 95.0% at -5 dB and remains above 80% at 0 dB. As the measurement quality improves, the failure probability decreases rapidly, reaching 10.5% at 10 dB and approaching zero for SNR values of 15 dB and above.

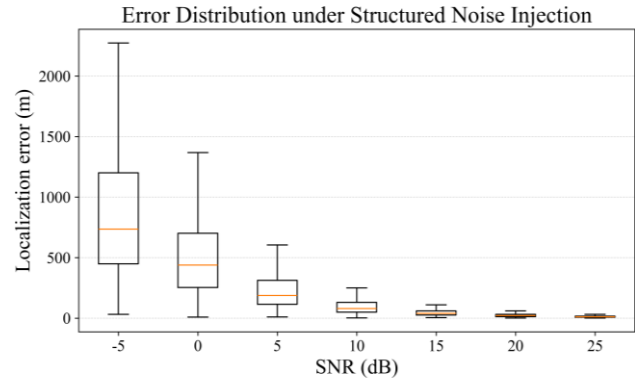


Figure 6. Distribution of localization errors across SNR levels.

The error distributions shown in Figure 6 provide additional insight into this behaviour. Under severe perturbation conditions, the localization errors exhibit large dispersion and significant variability across Monte Carlo realizations. In contrast, higher SNR levels produce considerably narrower distributions, indicating more stable and repeatable localization performance.

The combined failure rate and distribution analyses reveal that structured perturbations affect the localization system in a nonlinear manner. Rather than producing a gradual performance reduction, severe measurement degradations introduce intermittent localization failures and large error excursions. The main change from failure-prone to low-failure operation occurs between 5 dB and 10 dB.

To examine this interval at a finer resolution, an additional focused experiment is conducted between 5 dB and 10 dB using 1 dB increments. The five-sensor geometry, target location, structured perturbation parameters, weighted nonlinear least-squares estimator, and 200 m failure threshold remain unchanged. Each SNR level is evaluated using 600 Monte Carlo realizations. Only the SNR resolution is increased. The RMSE results are reported with 95% bootstrap confidence intervals, whereas Wilson intervals are used for the failure-rate estimates.

Figure 7 shows a continuous reduction in localization error across the focused interval. The RMSE decreases from 277.665 m at 5 dB to 120.310 m at 10 dB. Intermediate values of 243.329 m, 208.390 m, 170.194 m, and 140.652 m are obtained at 6, 7, 8, and 9 dB, respectively. The confidence intervals become narrower as the SNR increases, which is consistent with the reduced spread of the localization errors under lower perturbation levels.

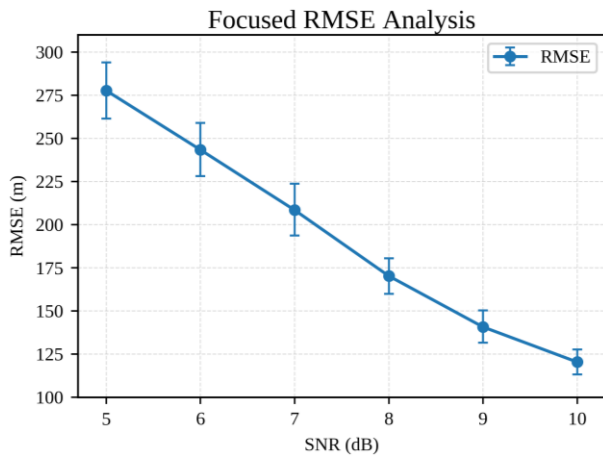


Figure 7. Focused RMSE analysis within the 5–10 dB interval.

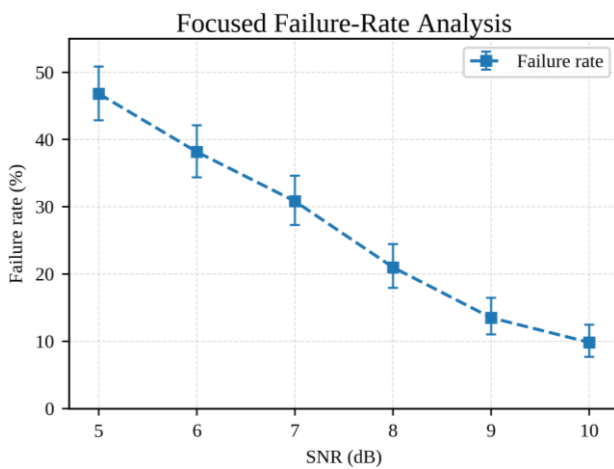


Figure 8. Focused failure-rate analysis within the 5–10 dB interval.

The failure-rate results in Figure 8 provide a similar trend. The failure rate decreases from 0.4683 at 5 dB to 0.0983 at 10 dB. Values of 0.3817, 0.3083, 0.2100, and 0.1350 are observed at the intermediate SNR levels. This corresponds to a reduction of 37.00 percentage points across the tested interval. The confidence intervals at 5 dB and 10 dB do not overlap, indicating that the observed change is larger than the Monte Carlo sampling variation.

The coarse-grid and focused tests place the main reliability recovery within the 5–10 dB interval. Both RMSE and failure rate decrease at each 1 dB step without changing the estimator or perturbation parameters. The focused test hence supports the presence of a concentrated transition region rather than a change caused by sparse SNR sampling. Under the tested five-sensor configuration it can be seen that the controlled noise injection can effectively expose reliability boundaries and information-deficient operating regimes in multisensor localization systems.

Conclusion

This study presents a structured noise injection framework for examining information degradation and reliability transitions in multisensor localization systems. A five-

sensor localization scenario is considered, where Gaussian perturbations, intermittent burst disturbances, and positive measurement biases are introduced into range measurements under different signal-to-noise conditions. Localization behaviour is evaluated through RMSE, FIM, CRLB, and failure rate metrics.

The results show that measurement degradation affects both localization accuracy and information availability. As perturbation severity increases, RMSE and failure probability increase, while the information content represented by the FIM decreases and the corresponding CRLB uncertainty increases. A pronounced transition region is observed between 5 dB and 10 dB, where localization failures decline rapidly and estimation accuracy improves substantially. These observations suggest that reliability degradation is not purely gradual and that information loss, uncertainty growth, and failure behaviour emerge concurrently within a limited SNR interval.

The novelty of this study lies in the use of structured noise injection as an information probe rather than as a test condition for a newly proposed estimator. Existing localization studies generally concentrate on reducing estimation error, suppressing outliers, compensating for non-line-of-sight bias, or deriving theoretical bounds under fixed error assumptions. Here, the sensor geometry and weighted nonlinear least-squares estimator remain unchanged, while Gaussian perturbations, intermittent burst events, and positive range biases are varied in a controlled manner. RMSE, failure rate, FIM, and CRLB are then evaluated together to reveal how information loss, uncertainty growth, and operational failure develop across the same SNR range. The focused 5–10 dB analysis further identifies a narrow interval in which reliability changes rapidly despite the unchanged estimator structure.

From an engineering perspective, the identified transition interval can support operating-limit selection in sensor-health monitoring, measurement rejection, recalibration, and adaptive sensing. Since the estimator and geometry remain fixed, the observed change can be attributed directly to measurement degradation within the tested five-sensor scenario.

Conflict of Interest

The author declares that there is no conflict of interest.

Statement of Research and Publication Ethics

The author declares that this study complies with research and publication ethics. Since the study is based on a simulation-based multisensor localization model and does not involve human participants, animals, personal data, or clinical material, ethics committee approval is not required.

Author Contribution Statement

The author solely contributed to conceptualization, methodology, software, formal analysis, visualization, writing, original draft preparation, review and editing.

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