

# Error Correction Using Bayesian GRU Network in Hybrid Visual Inertial Navigation System

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**Abstract:** Vision-based navigation systems (VINS) are increasingly utilised as an alternative to GNSS for UAVs operating in urban environments but suffers from performance degradation under visual fault conditions like illumination variation, rapid motion, texture-less environments, and weather effects. While hybrid architecture incorporating Kalman filters and machine learning (ML) improves performance, they often lack evidence of providing contingency for non-Gaussian error distributions, limiting operational safety. To address these shortcomings, an enhanced hybrid VINS architecture is proposed featuring a Bayesian GRU-based error correction network (B-GRU) providing a contingency while compensating model errors. To the best of the author's knowledge, this is the first attempt to estimate uncertainty using B-GRU compensator while addressing data uncertainty for VINS applications. The system architecture integrates an Error-State Kalman Filter (ESKF) and the B-GRU, compensating for position errors with uncertainty prediction. The proposed approach is validated using datasets from MATLAB incorporated Unreal Engine simulated environment, replicating the complex fault conditions. The ML model is trained on various visual failure modes to adapt the variability in the signal patterns during flights with simulated datasets and tested across varied flight paths and lighting scenarios. Results demonstrate that the fusion strategy effectively corrects erroneous measurements arising from corrupted sensor data and imperfect models and achieves improvement of 78.06% compared to SOTA hybrid VIO in horizontal axis while capturing complex flight dynamics in unseen environment. Comparative analysis demonstrates the effectiveness of B-GRU in mitigating failure modes with predictive error boundary, achieving a 72% improvement in performance compared to the architecture that integrates GRU-based error compensation. This approach shows a step forward in enhancing positioning accuracy and contingency in challenging urban environments.

**Keywords:** Error compensation; Visual Inertial Odometry; Bayesian GRU; Failure modes; Error State Kalman Filter; Uncertainty

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## 1. Introduction

Urban Air Mobility (UAM) aims to establish a safe and efficient system for short-range air transportation, utilising highly automated aircraft to carry transport passengers or cargo at lower altitudes within urban environments. Operational safety remains the top priority, with navigation safety being a critical prerequisite [1]. A significant challenge in urban navigation is ensuring the reliability of core sensors like the Global Navigation

Satellite System (GNSS) for PNT. In urban canyons, GNSS signals are frequently affected by factors such as no-line-of-sight (NLOS) and multipath effects, necessitating the integration of alternative sensors with GNSS to achieve accurate positioning [2]. Vision-based navigation systems (VINS) are increasingly utilised as an alternative to GNSS for UAVs operating in urban environments, offering a promising solution to address navigation challenges [1]. Performance degradation is attributed to the current state-of-the-art systems in complex scenarios due to visual fault conditions like illumination variation, rapid motion, texture-less environments, and weather effects [3], [4]. A common approach to improving navigation integrity involves incorporating fault detection in feature-based visual odometry (VO) algorithms. However, these methods often struggle to bound errors arising from various sources of measurement uncertainties in urban environments [1], [5]. To address these challenges, hybrid architectures have been integrated into VIO systems to compensate for errors in corrupted VO sensors and Kalman filter (KF) model measurements using machine learning (ML), thereby enhancing performance while accounting for various source of uncertainties under complex urban environments [6]. While hybrid architectures incorporating Kalman filters and machine learning (ML) improve performance, they lack evidence of providing contingency for non-Gaussian error distributions, limiting operational safety.

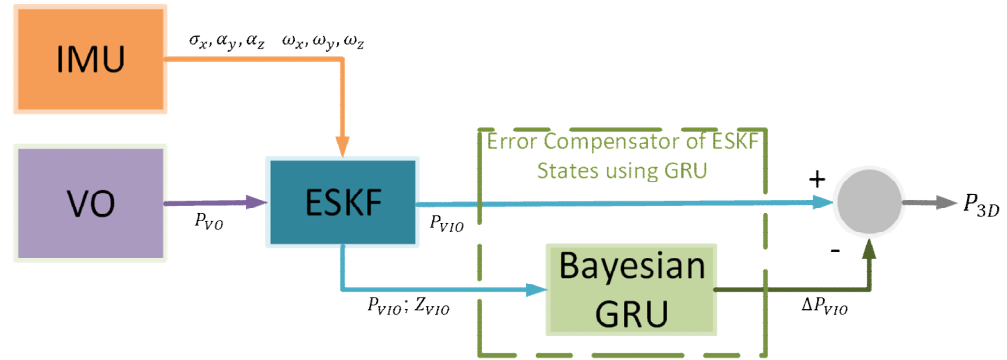
Deep learning methods like LSTM with Monte Carlo Dropout [7] variational autoencoders (VAEs) [8] and RCNN with mixture density network [9] estimate pose with confidence but lack robust statistical guarantees in visually degraded environments. Furthermore, current state-of-the-art involving such architectures face challenges, including reliance on large datasets [4], performance degradation in out-of-distribution test scenarios and insufficient uncertainty estimation [7], [8], [9]. To address these shortcomings, an enhanced hybrid VINS architecture is proposed featuring a Bayesian Gated Recurrent Unit (GRU)-based error correction network (B-GRU) providing a contingency while compensating for model errors. To the best of the author's knowledge, this is the first attempt to estimate uncertainty using the B-GRU compensator while addressing data uncertainty for VINS applications. The system architecture integrates an Error-State Kalman Filter (ESKF) and the B-GRU, compensating for position errors with uncertainty prediction. This research employs a B-GRU for efficient, real-time uncertainty estimation in navigation, offering a simpler, faster alternative to more complex Bayesian LSTM and Bayesian Bi-LSTM model by leveraging Monte Carlo Dropout (MCD) for uncertainty quantification. The formulation is extended by providing the out-of-the-distribution analysis by conducting the comparative analysis based on datasets collected from two different environments replicating fault conditions: a photorealistic environment built with MATLAB incorporated Unreal Engine, and EuRoc datasets [10] covering a complex indoor environment in real-time.

The remainder of this study is structured as follows: Section 2 includes the proposed system architecture with a brief description. Section 3 discusses experimental settings for data generation to train and test the solution. Section 4 discusses the test and performance analysis of the proposed approach under different scenarios with comparisons. Finally, the conclusion is presented in Section 5.

## 2. Proposed Bayesian GRU Error Correction-aided Hybrid Visual Inertial Navigation System

This section presents a high-level overview of the proposed novel framework of hybrid VIO, while monocular camera images are used to estimate VO position using feature-based VO algorithm [11]. The fusion architecture fuses the VO estimated position with IMU estimated raw linear acceleration and angular velocity using ESKF to estimate VIO

position. To correct ESKF estimated measurements errors caused by model uncertainty, B-GRU predicts position increments with confidence measure that provides error boundary of the faults presents in the environment, thereby enhancing VIO performance by reducing epistemic uncertainty. Figure 1 presents a high-level diagram of the proposed hybrid VIO by utilising error correction mechanism with confidence measures.



**Figure 1.** Proposed hybrid architecture for VIO with confidence measure.

### 2.1. Bayesian GRU-aided Error Correction

Bayesian-GRU integrates Bayesian interface into GRU neural network by replacing fixed weight estimates with probability distributions, enabling uncertainty quantification in predictions. This approach enhances the model's robustness and improves generalisation capabilities. This study introduces a single layer of GRU incorporating MCD sampling method in Bayesian interface based on an extensive study that emphasised MCD's balance of accuracy and computational efficiency [12]. The MCD technique mitigates overfitting by randomly dropping nodes during the training process, effectively setting their connected weight to zero. During inference, MCD algorithm operates multiple stochastic forward passes through a neural network for a given input  $x$ , applying dropout with a specified probability to randomly deactivate a fraction of units during each pass. This results from a set of outputs,  $y$  from the multiple passes, and the final prediction is obtained by averaging these outputs as shown in the equation (1). The associated uncertainty is estimated from the sample distribution with  $T$  forward passes chosen sufficiently large to ensure statistical significance.

$$y = \frac{1}{T} \sum_{t=1}^T y_t \quad 1$$

It is crucial to select input and output for the ML module since parameters are directly determine the training efficiency and navigation accuracy. B-GRU is applied to compensate for measurement model errors associated with the imperfection of the model due to manual tuning and nonlinearity presents in the data. The  $\Delta P_{VIO}$  model predicts position error between ESKF measured position and ground truth with the input parameters ESKF estimated position and innovation i.e. the difference between the predicted observations and observed value in the NED frame. The Bayesian GRU model error compensator learns from the state-evaluation process and associated uncertainties, MCD dropout facilities model uncertainty estimation utilizing 500 samples to provide reliability of estimated mean and 99.7<sup>th</sup> percentile or  $3\sigma$  confidence interval (CI). Notably, the increment of ESKF-VIO is selected as ground truth in these cases for evaluation of the prediction of Bayesian GRU model.

### 2.2 Hybrid VIO Navigation System

The proposed novel architecture is designed with a combination of B-GRU error correction and ESKF to estimate improved positioning performance under dynamic conditions.

The ESKF formulation is based on the previous work [13]. In this formulation, the UAV state  $x$  is defined as-

$$x = [p \ v \ q \ \alpha_b \ \omega_b]^T \quad 2$$

Where,  $p = [p_N, p_E, p_D]$ - represents the position in the platform;  $v = [v_N, v_E, v_D]$ - platform's velocity;  $q = [q_N, q_E, q_D]$ - represents orientation in the form of quaternion;  $\alpha_b = [\alpha_{b_N}, \alpha_{b_E}, \alpha_{b_D}]$ - represents accelerometer drift and  $\omega_b = [\omega_{b_N}, \omega_{b_E}, \omega_{b_D}]$ - gyroscope drift accordingly. The main concept of the ESKF fusion strategy consists of the separation of the state vector into two parts: nominal state  $x$ , and error state  $\delta x$ .

$$x_k = x + \delta x \quad 3$$

Notably, the frame of references used to develop navigation equations for state estimation of ESKF follows the north-east-down (NED) frame format. The measurement update equations are derived as

$$K = \hat{P}_{k-1} H^T (H \hat{P}_{k-1} H^T + R)^{-1} \quad 4$$

$$\delta \hat{x} = K(y_k - h(\hat{x}_t))$$

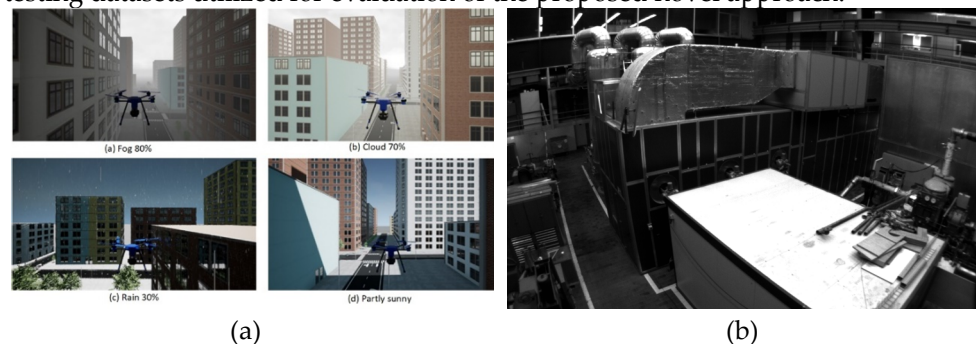
$$\hat{P} = (I - KH)\hat{P}_{k-1}$$

Finally, ESKF measurement position is corrected following equation and estimate improved proposed hybrid VIO position.

$$P_{VIO-corrected} = P_{VIO} - \Delta P_{VIO} \quad 5$$

### 3. Experimental Setup and Dataset Generation

This section outlines the experimental setup to evaluate the performance of the proposed B-GRU-aided hybrid VIO. The experimental setup utilised in this research has been adopted from previous work [11] which was implemented in MATLAB-incorporated Unreal Engine simulated urban environment to stimulate the data collection process for training and testing purposes. The simulated datasets involve diverse challenging conditions, including illumination variation, rapid motion, altitude variation, no-texture, and weather effects for shorter and extended flights. A monocular camera (720x1280 px, 10 Hz, 1109 px focal length) and simulated IMU (ICM 20649 at 100 Hz) were used. This study only investigates sunny weather conditions and compares performance against prior work. Additionally, Euroc dataset is utilized to assess generalization with estimation of error boundary under unseen environment. Figure 2 illustrates examples of training and testing datasets utilized for evaluation of the proposed novel approach.



**Figure 2.** Example of two different testing environments used for performance evaluation (a) MATLAB simulated urban environment (b) dark machine room collected in Euroc Dataset

#### 3.1 Training Phase

The ML modules are trained with 12 trajectories in sunny weather conditions replicating fault scenarios like flight dynamics, environmental structures and illumination variations

that can trigger multiple sources of data and model uncertainty within the navigation system involving imperfect modelling, sensor noise, data association errors, feature tracking errors and feature location errors mentioned in [11]. This diversity allows the model to learn and adapt to different fault conditions, improving overall performance and generalization ability in the presence of multiple fault conditions. Notably, this research has utilized GRU-aided KF model correction in Hybrid VIO architecture [11] from previous study for comparison. The proposed B-GRU is optimized and trained using 'TensorFlow Keras' Bayesian optimization tuner, selected for its superior accuracy over other tuning methods based on extensive review conducted using simulated datasets. A fully connected layer outputs predicted increments with uncertainty estimation using 500 Monte Carlo samples. The model uses a batch size of 128, Monte Carlo dropout rate of 0.2, Relu activation function and Relu recurrent activation function and the ADAMAX optimizer to minimize the discrepancies between the predicted and actual errors using mean squared error (MSE) loss.

### 3.2 Testing Phase

The testing dataset is designed with a combination of seen and unseen fault scenarios which are different from training datasets. During the testing phase, ML models operate in the prediction phase, remaining active throughout the experiment. The trained Bayesian GRU measurement error compensator predicts KF estimated position error with uncertainty based on KF predicted position and observation differences from the measurement model in the current navigation frame.

### 3.3 Uncertainty Metrics

A good uncertainty estimation model should provide uncertainty interval (UI) that are as small as possible, at the same time including ground truth value. In this study, Bayesian GRU is predicting model error uncertainty where the ground truth value is the position error (PE) associated from ESKF-VIO. The mean and  $3\sigma$  confidence boundary are selected to evaluate the model capturing uncertainty in error distribution of target data.

## 4. Performance Evaluation

To evaluate the performance and adaptability of the proposed novel hybrid VIO framework, two experiments are carried out using two different testing environments with varying lighting conditions: 1) out-of-the-distribution analysis to evaluate model adaptability in unseen complex environment, 2) performance evaluation under scarcity of features fault condition with varying lighting.

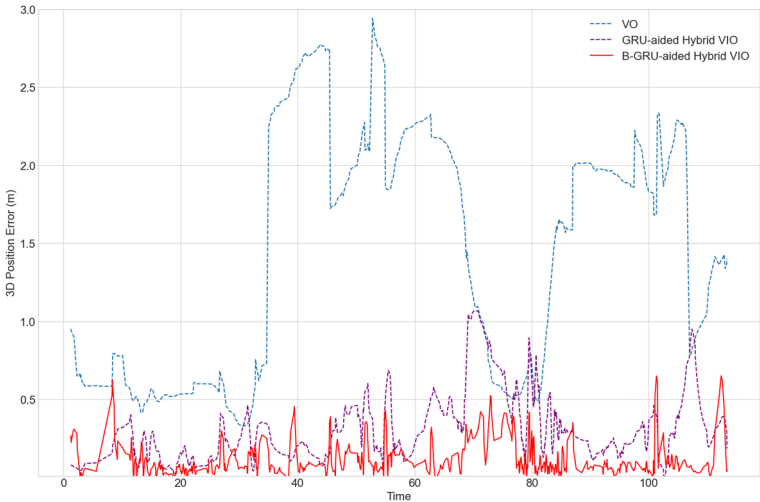
### 4.1 Out-of-the-distribution problem:

The experiment is designed to prove the quality of uncertainty prediction intervals with performance improvement provided by proposed approach. In order to show an empirical comparison with SOTA on uncertainty estimation with performance improvement, the study selects Euroc dataset, specially MH05\_difficult for benchmarking. Euroc dataset was collected with MAV flying in indoor environments leveraging complex scenarios i.e. darkness, illumination variation, rapid motion, and blur. The B-GRU model was trained on MATLAB environment to provide insight into the adaptability of the model to an unseen complex environment. Table 1 presents the comparative results for MH\_05 sequence in Euroc dataset. It is observed that the proposed framework constantly outperforms existing methods in terms of pose estimation accuracy and CI. Difficulties arise from harsh motion dynamics, increased degree of freedoms and image blur. Notably, the architectures from SOTA deep learning and hybrid VIO methods are selected for comparative analysis as they were evaluated using similar dataset. The proposed method has effectively mitigated erroneous measurements arising from various sources of uncertainty as

illustrated in Figure 3 and showed improvement in 33.8% compared to GRU-aided hybrid VIO and 78.06% compared to SOTA hybrid VIO [4] for 3D. In contrast, SOTA architectures suffered from performance degradation above 1 m in 3D position due to insufficiency in adapting the dynamics presents in the data e.g. Self-VIO [3] while using all the series of Euroc datasets for training their models. While this approach helps achieving centimetre level accuracy by addressing challenges like presence of rapid motion and motion blur in the flight that led to feature tracking errors and feature location errors, it struggles to maintain confidence boundaries required [7] for uninterrupted flight integrity. In contrast, this study evaluates the proposed solution on the full dataset without split and demonstrates significant improvement and more robust the induced outliers.

**Table 1** Comparison with SOTA methods that used MH05\_deficult sequence from EuRoc dataset.

Techniques	RMSE (m)				Horizontal RMSE (m)	3D 95 <sup>th</sup> Percentile (m)	3σ (OR%)			3σ (OR%)
	N	E	D	3D	3D		N	E	D	3D
End-to-End VIO [4]	-	-	-	1.96	-	-	-	-	-	-
DeepVIO [14]	-	-	-	0.52	-	-	-	-	-	-
Self-VIO[3]	-	-	-	0.29	-	-	-	-	-	-
UA-VO [7]	-	-	-	-	-	-	-	-	-	21.95
ESKF-VIO	1.75	0.96	0.87	1.94	1.45	1.63	35.5	39.4	29.2	-
GRU-aided Hybrid VIO [11]	0.40	0.65	0.16	0.65	0.56	0.71	-	-	-	-
B-GRU-aided Hybrid VIO	0.29	0.44	0.10	0.43	0.37	0.56	16.0	17.9	17.6	-



**Figure 3.** 3D position error estimated using MH05\_difficult seq. from EUROC dataset with multiple sources of aleatoric uncertainty

Figure 4 represents the proposed model’s ability to capture the uncertainty, providing an uncertainty boundary in each coordinate in the MH\_05 sequence of Euroc dataset. The existing solution [7] explored 3D position for uncertainty boundaries by replacing observations with Gaussian noise and estimating 3σ boundaries. Thus, this study has utilised 99.7<sup>th</sup> percentile or 3σ uncertainty intervals (UI) for comparison. There is a gap in evaluating the performance of models using the entire EuRoc dataset due to the complexity of the data (darkness, rapid motion, vehicle dynamics). Unlike existing solutions concerning uncertainty in VO systems[7] where the EuRoc sequence was split into 100 test samples, this study evaluates the performance of on entire datasets involving 2273 frames, 22212



samples in IMU data. The proposed method has effectively predicted error boundary compared with ESKF-VIO and mitigated erroneous measurements arising from various sources of uncertainty, with the improvement of UI of 55% in N, 55% in E and 40% in D coordinate. Additionally, it demonstrated approximately 16.0% in N, 17.9% in E and 17.6% in D coordinate of data remain out of range (OR) compared to ESKF-VIO PE.

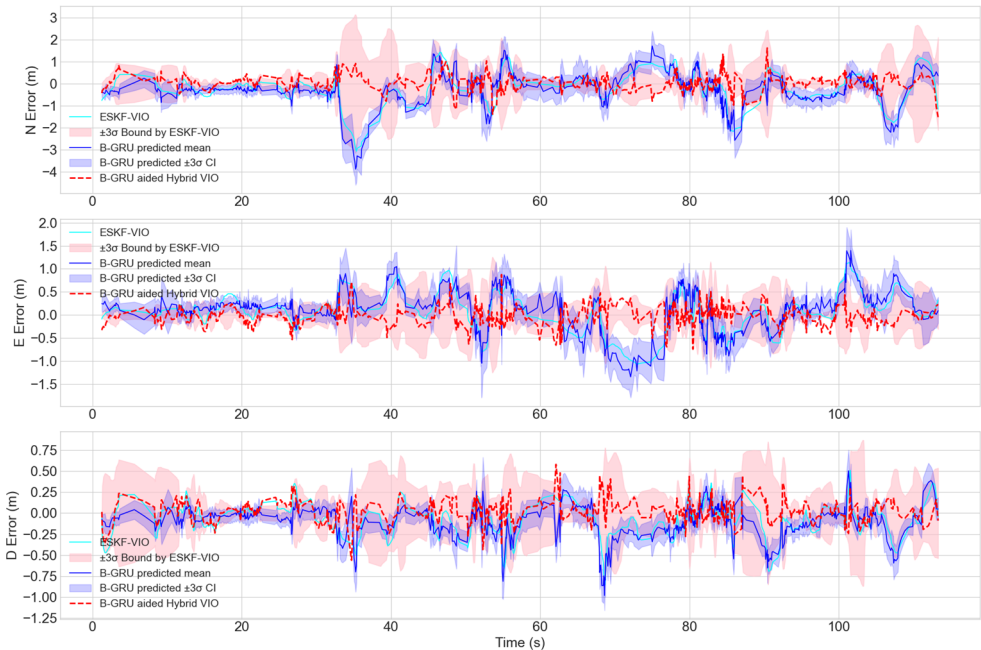


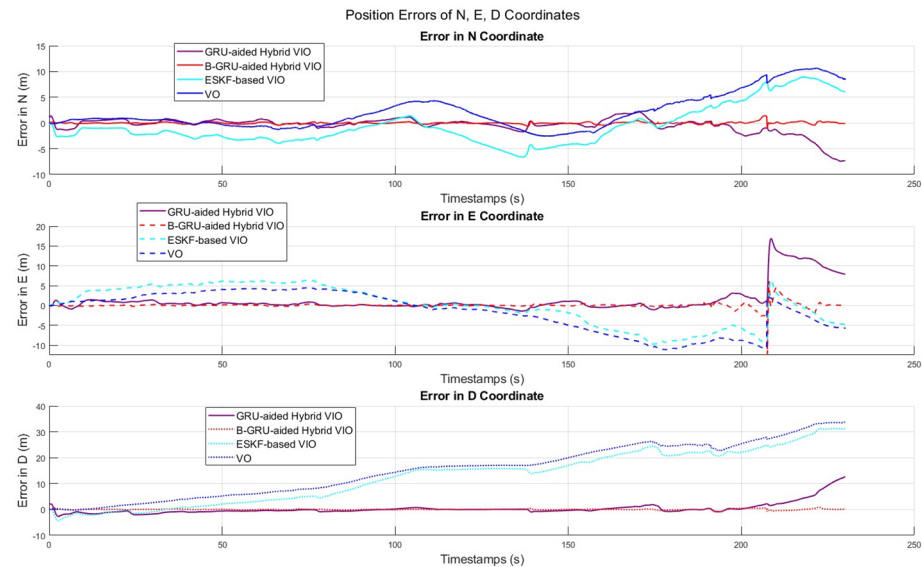
Figure 4. Uncertainty estimation in EuRoc MH05- difficult dataset

5.2 Performance evaluation under fault conditions

This section evaluates the proposed approach’s effectiveness in enhancing trajectory accuracy under complex flight dynamics including texture-less environment. using unseen test data from the same simulation environment . The selected trajectory includes high dynamics and starting from new location excluded from training data, aligning with previous work [11]. As illustrated in Figure 5, the proposed approach outperforms reference systems across all coordinates. After 200s, performance degradation is observed in N & E direction across VO, ESKF-VIO and GRU-aided hybrid VIO reference systems , primarily due to corrupted sensor measurements and feature tracking errors caused by rotation with vibration during landing. These effects highlight the impact of aleatoric uncertainty and model mismatch in dynamic scenarios. The proposed approach significantly reduces long tails, achieving horizontal 95<sup>th</sup> percentile errors of 3.1811m, as shown in Table 2 and achieving a 64% improvement over GRU-aided hybrid VIO and a 75% improvement over traditional ESKF-VIO under complex conditions.

Table 2 RMSE and 95<sup>th</sup> percentile summary of the performance under unseen scenario

Techniques	RMSE (m)				95 <sup>th</sup> Percentile				
	N	E	V	3D PE	Horizontal PE	3D PE	Improvement	Horizontal PE (m)	Improvement
VO	4.04	5.13	18.11	27.56	6.53	33.20	-	11.36	-
ESKF-based VIO	3.7	4.83	16.00	24.19	6.15	29.63	40%	9.01	21%
GRU-aided Hybrid VIO [11]	1.76	3.46	1.96	4.31	4.16	11.34	66%	12.12	-
B-GRU-aided Hybrid VIO	1.350	0.649	0.990	3.13	1.4976	3.7519	88%	3.1811	72%



**Figure 5.** Position error along with each axis in the presence of scarcity of features fault condition

## 5. Conclusion

This study presents a proposed hybrid VIO integrated with B-GRU measurement error compensation that significantly address model uncertainty and provides CI of bounded errors to enhance navigation integrity in complex scenarios. Using MCD sampling the model captures uncertainty from visual degradation, flight dynamics, and sensor noise, providing  $3\sigma$  CI of errors present in the navigation environment. A series of experiments were conducted to validate the proposed approach under unseen diverse conditions including challenging light and high flight dynamics. The solution is able to capture induced visual sources of uncertainties such as feature extraction error, feature tracking error, data association error, mismatch in dynamic, imperfect modelling compared to ESKF-VIO and provide  $3\sigma$  UI improvement approximately 50% in horizontal coordinate i.e. indoor (Euroc). Another experimental result highlights the proposed framework's ability to mitigate position uncertainty while removing additional induced unmodelled noise, even when sensor data is corrupted, or the model is imperfect, achieving 72% improvements (simulated urban environment). In summary, the combined performance and uncertainty gain estimates indicate the proposed framework offers a promising vision-based A-PNT solution for safe and reliable UAV navigation under complex urban environments. This research is step forward towards integrity monitoring using AI. Future work will focus on extending validation to real-time outdoor flights.

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