



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

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Introduce uncertainty in data association

SOTA - degradation scenarios

Visual Inertial
Odometry

Complementary
Solution



Dense urban environment



Illumination variation (lighting effects and reflections)



Different time of the day with a low-texture environment (sky-view where fewer features are available to extract)



Weather conditions (blur and hazy features causing feature tracking issue)



Low-texture environment (camera pointing to white wall- no feature to extract)

Combination of motion variation and limited field-of-view fault factors

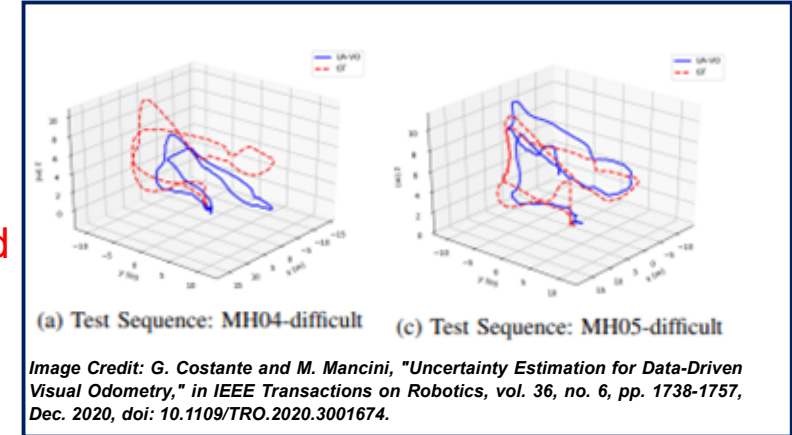
- GNSS vulnerability
- Operation safety and efficiency
- Collision and crashes

Lack of statistical background, particularly when dealing with non-Gaussian error distributions, where a 3σ uncertainty interval (UI) cannot ensure an error boundary in visually degraded environments

Data-Driven VIO

- Dependency on **data variability**
- **Vast training datasets** for CNN architectures
- **Inefficient uncertainty** estimation
- Introduced long tail issues
- Struggle to **generalise** beyond the initial training set

Sources of uncertainty arise when the test and training data are mismatched and introduce outliers



EuRoC Example

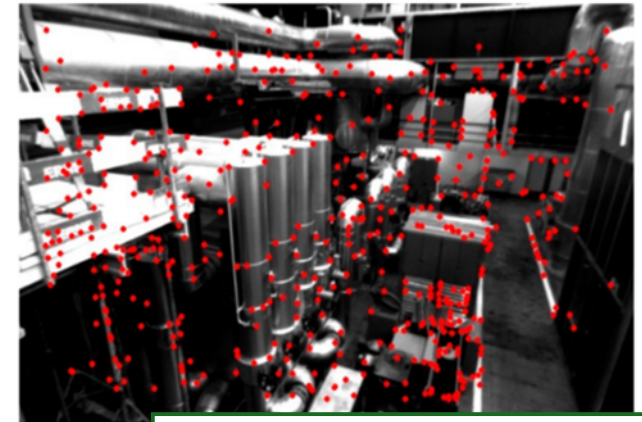
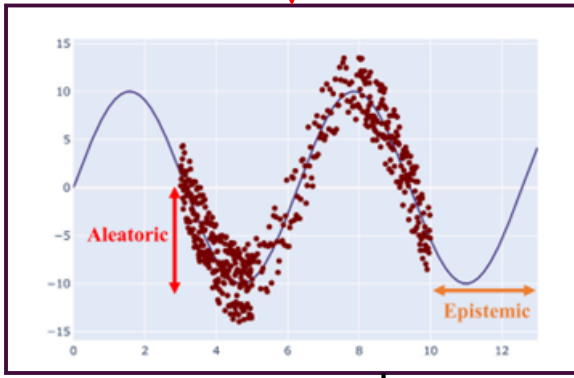


Image Credit: Aladem, Mohamed & Rawashdeh, Samir. (2018). *Lightweight Visual Odometry for Autonomous Mobile Robots*. *Sensors*. 18. 2837. 10.3390/s18092837.

Hybridization in VIO

Error compensation using hybridization with ML:

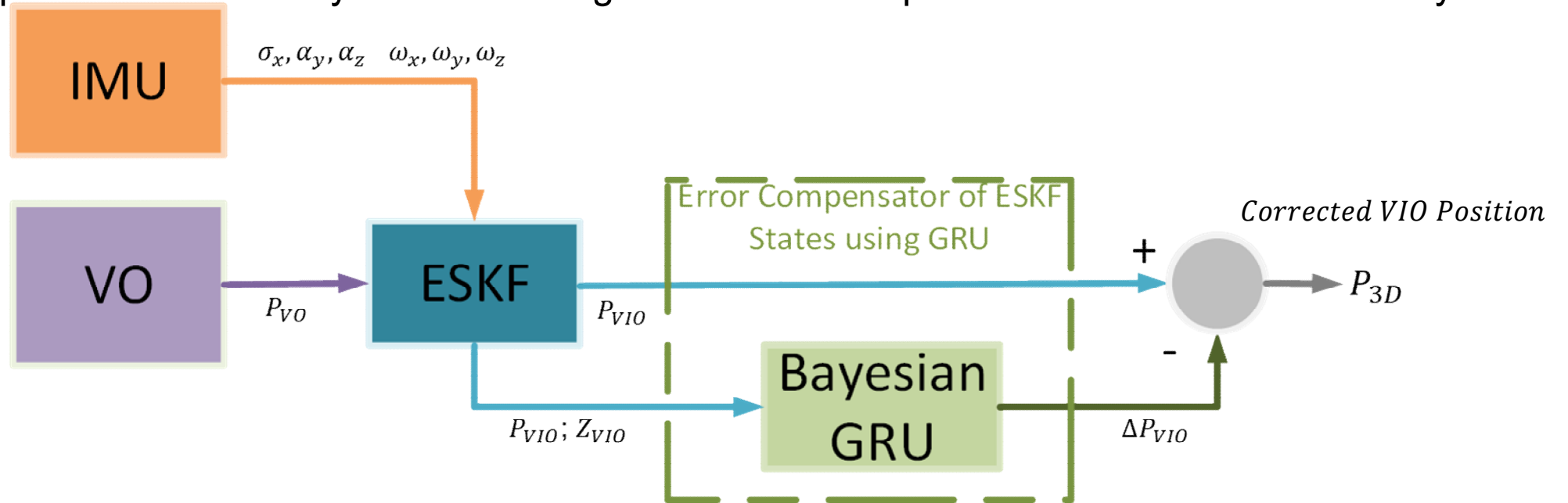
- Allows an improvement of handling of complex scenarios by targeting the sources of uncertainty
- Enables better mitigation of sensor noise, corrupted measurements, model imperfections and assumptions
- Quantifying errors remains an open issue



Aleatoric uncertainty present in data
Epistemic uncertainty present in models

Proposed Architecture

- This integrates an Error-State Kalman Filter (ESKF) and the B-GRU, compensating for position errors with uncertainty prediction
- Provides epistemic uncertainty intervals using mean and 95th percentile confidence boundary



- Bayesian GRU is predicting model error uncertainty with an input from the position error (PE) of the ESKF-VIO
- Monte Carlo Dropout (MCD) for uncertainty quantification

EKF vs ESKF

- ESKF uses raw IMU measurements to update state information
- EKF uses the position from INS
- ESKF use the quaternion estimation model to handle rotations effectively
- ESKF has error state estimation in measurement steps, making it more stable than EKF

The state vector - $x = [p \ v \ q \ \alpha_b \ \omega_b]^T$

Updated error states and state covariance

$$\delta \hat{x} = F_x(x, u_m) \cdot \delta \hat{x}$$

$$x_k = x_{k|k-1} \oplus \delta \hat{x}_k$$

$$x_k = x_{k|k-1} + k_k(z_k - H_k x_{k|k-1})$$

$$P = F_x P_{k-1} F_x^T + F_i Q_i F_i^T$$

The transition matrix for the error state as follow-

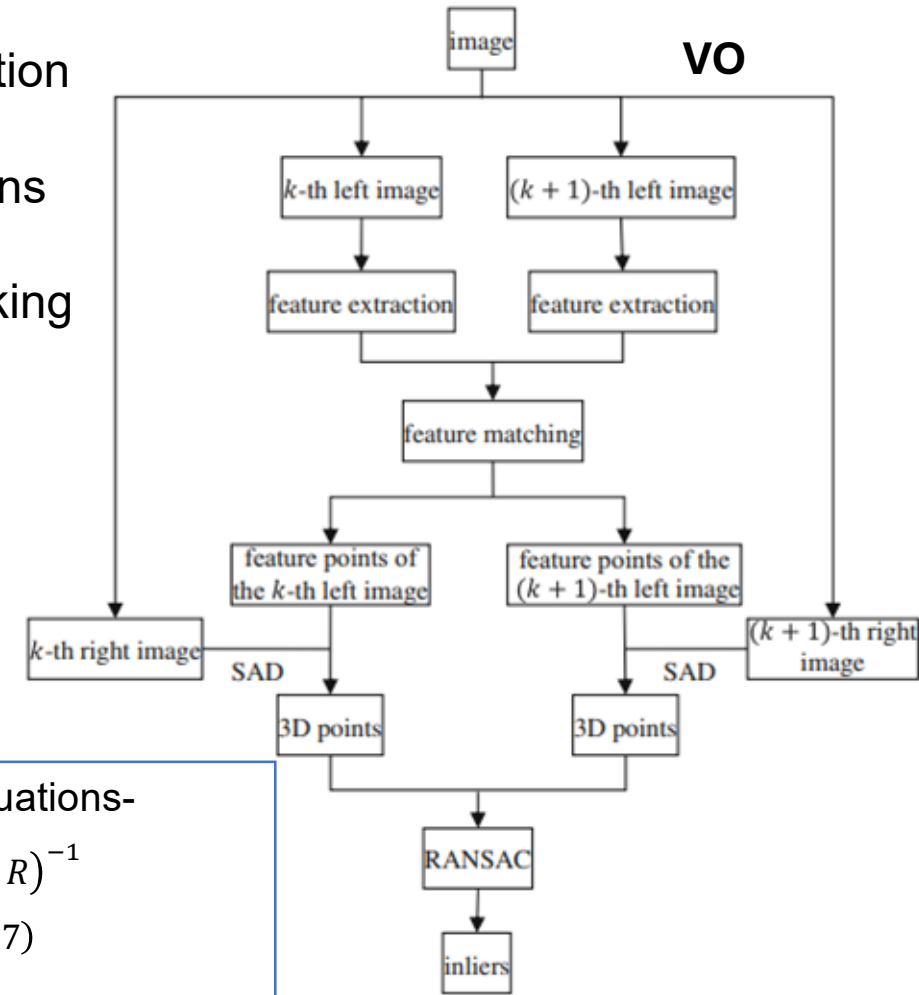
$$F_x = \frac{\partial f}{\partial \delta x} \bigg|_x = \begin{bmatrix} I & I\Delta t & 0 & 0 & 0 \\ 0 & I & -R[a_m - a_{b_k}]_x \Delta t & -R\Delta t & 0 \\ 0 & 0 & R^T \left\{ ((\omega_m - \omega_{b_k}) \Delta t) \right\} & 0 & -I\Delta t \\ 0 & 0 & 0 & I & 0 \\ 0 & 0 & 0 & 0 & I \end{bmatrix}$$

The measurement update equations-

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

$$\delta \hat{x} = K(y_k - h(\hat{x}_t)) \quad (7)$$

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



Bayesian GRU

- Improves generalisation capabilities
- Incorporates MCD to mitigate overfitting by randomly dropping nodes during the training process

Conventional GRU gates are written as-

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

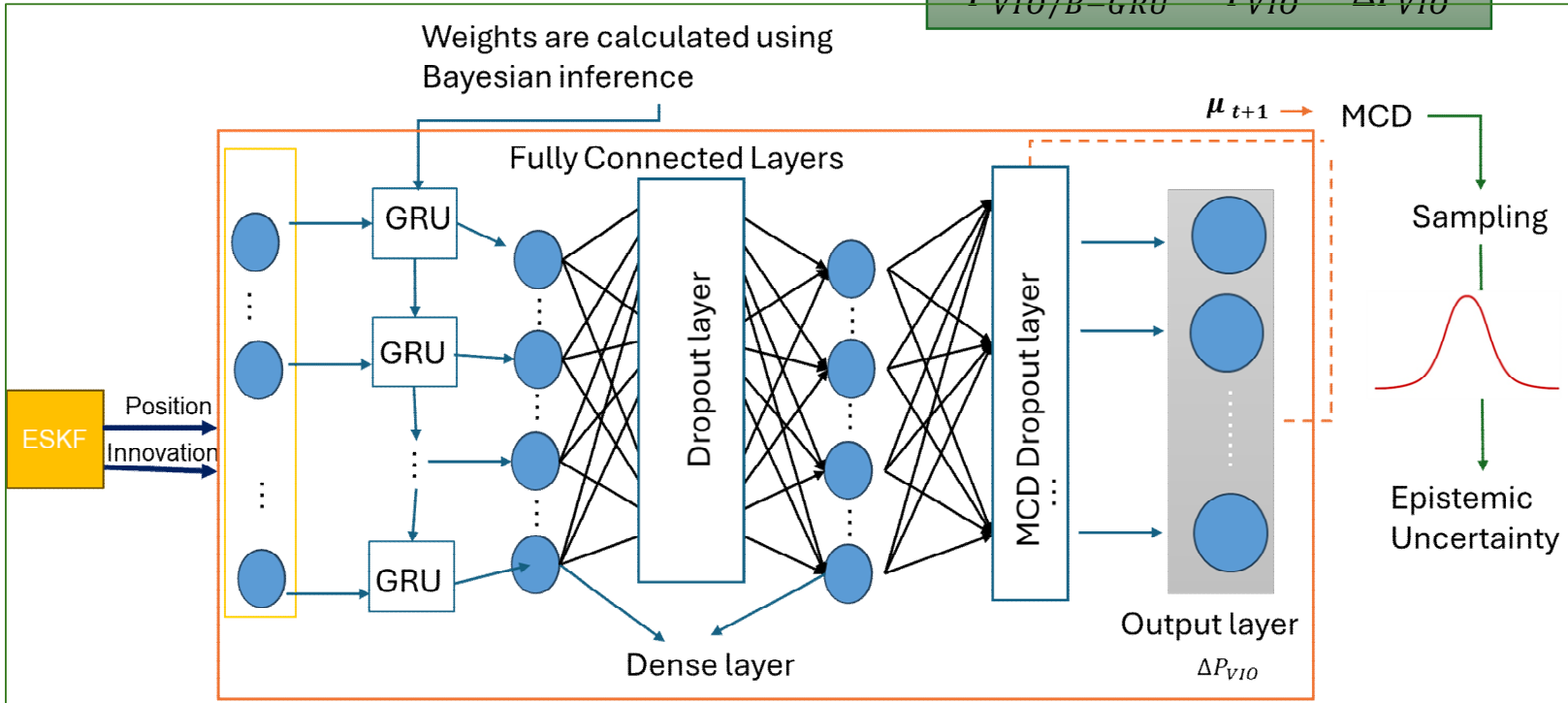
$$\tilde{h}_t = \tanh(W \cdot [r_t^* h_{t-1}, x_t])$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t$$

Errors in predicted states are compensated with estimation of error boundary

Bayesian inference is applied to calculate the posterior $p(W|D)$ over the network weights W -

$$p(W|D) = \frac{p(D|W)p(W)}{p(D)}$$



B-GRU Architecture

GRU Single layer

Dense layers-3

Hidden layers- chosen based on hyperparameter tuning

Relu activation function

Relu recurrent activation function

Batch size-128

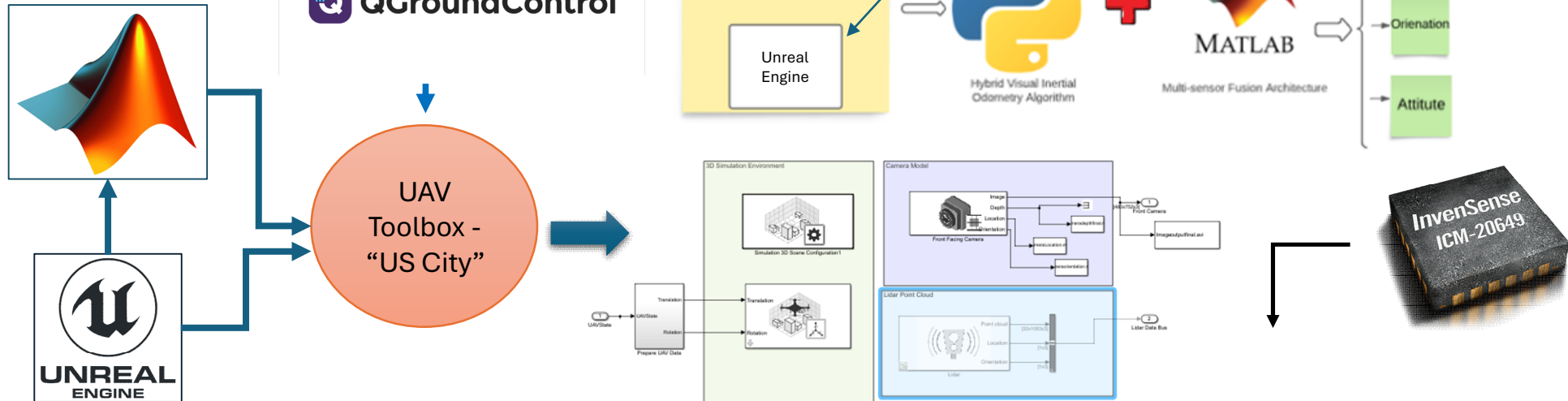
Adamax optimiser

Loss function - Mean Squared Error (MSE)

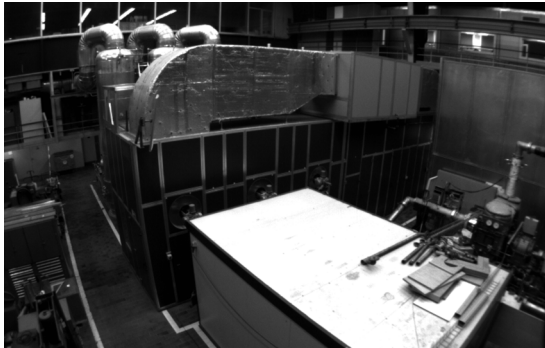
MCD 0.2

MCD samples 500

Data Collection



Forward-facing camera: 720 × 1280, 10 Hz



EuRoC

MATLAB simulated IMU specs

- Accelerometer Bias Stability 0.014 $m/s/s$
- Gyroscope Bias Stability 0.0025 rad/s
- Angle Random Walk 0.00043633 $rad/s/s * \sqrt{Hz}$
- Velocity Random Walk 0.0012356 $m/s/s * \sqrt{Hz}$

Training Dataset

Fault Factors used in training trajectories

Urban Settings

Fight Dynamics (Trajectory)

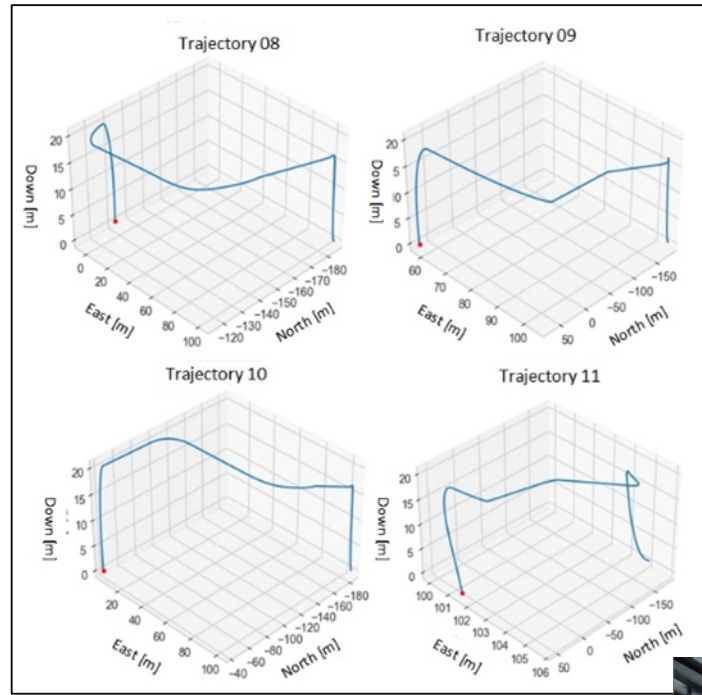
- Speed Variation
- Altitude Variation
- Sudden pause in middle of flight
- Overlapping route
- Longer flight duration
- Short flight duration
- Turn
- Jittering
- Diagonal rotating route
- Temporary deviation
- Motion variation

Illumination variation

- Harsh light
- Overexposure
- Low-moon light
- Reflection of window glass
- Rapidly changing illumination
- Combination of shadows of objects
- Dark Shadows of objects
- Lens flare

Environmental Structure

- Features wall
- Low-texture
- Short building
- Tall building
- Moving objects
- Limited field of View
- Narrow pathways



Example of Training Trajectory

12 trajectories for training

Replicating sources of uncertainty within data

Split training datasets to learn GRU about turns

Flight duration 12-15 mins for each trajectory

Sunny weather condition

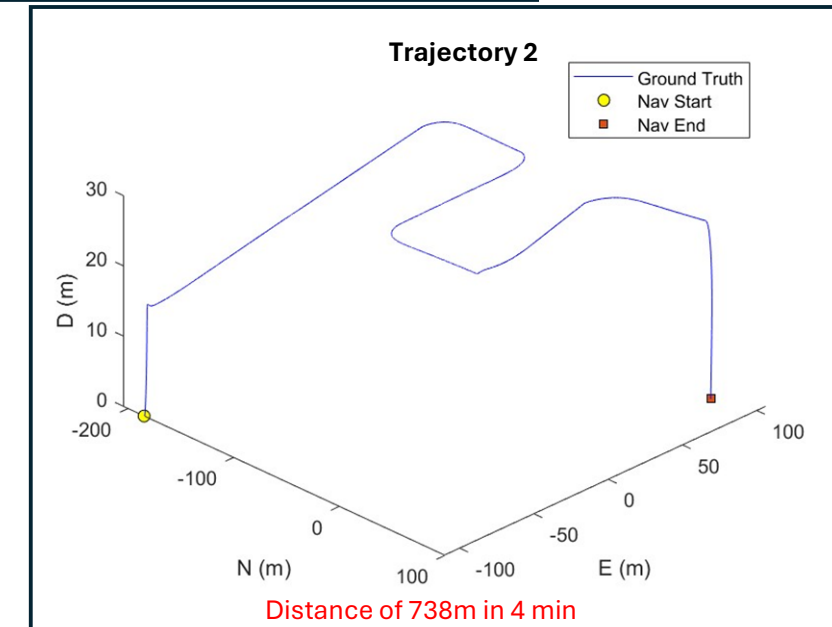
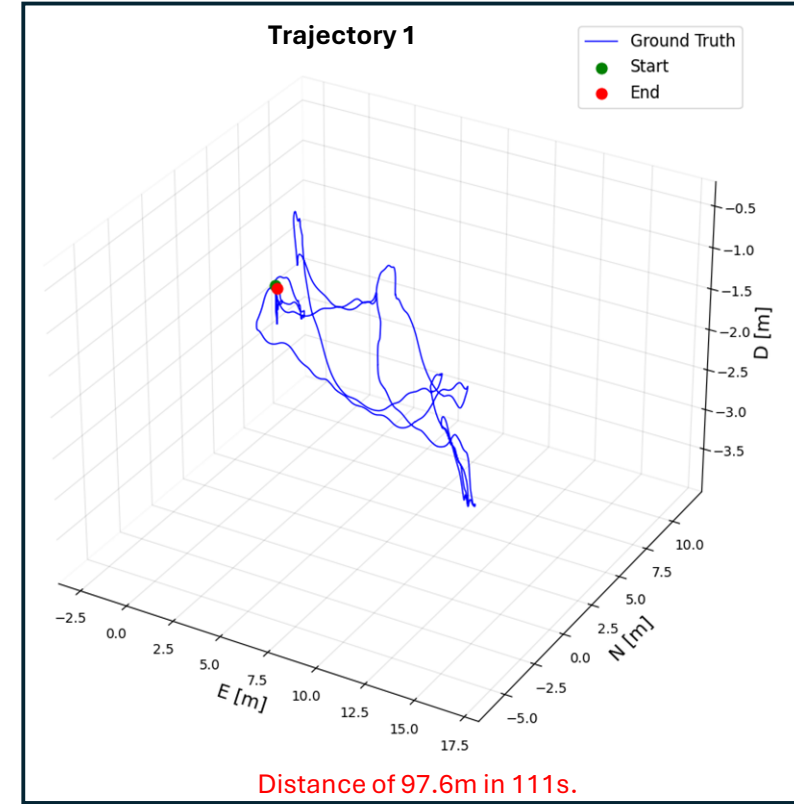


Performance Evaluation

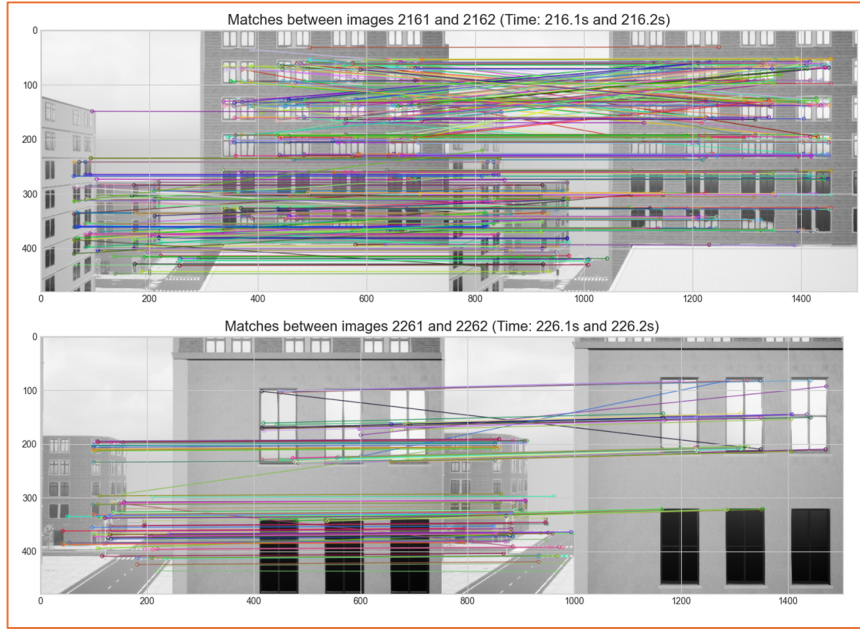
Testing description-

- Test trajectories were not part of the training data
- Out-of-distribution analysis on different testing environments (EuRoC)
- Chosen to evaluate the variability and adaptivity of the hybrid system
- GRU inference time ~ 0.2 ms

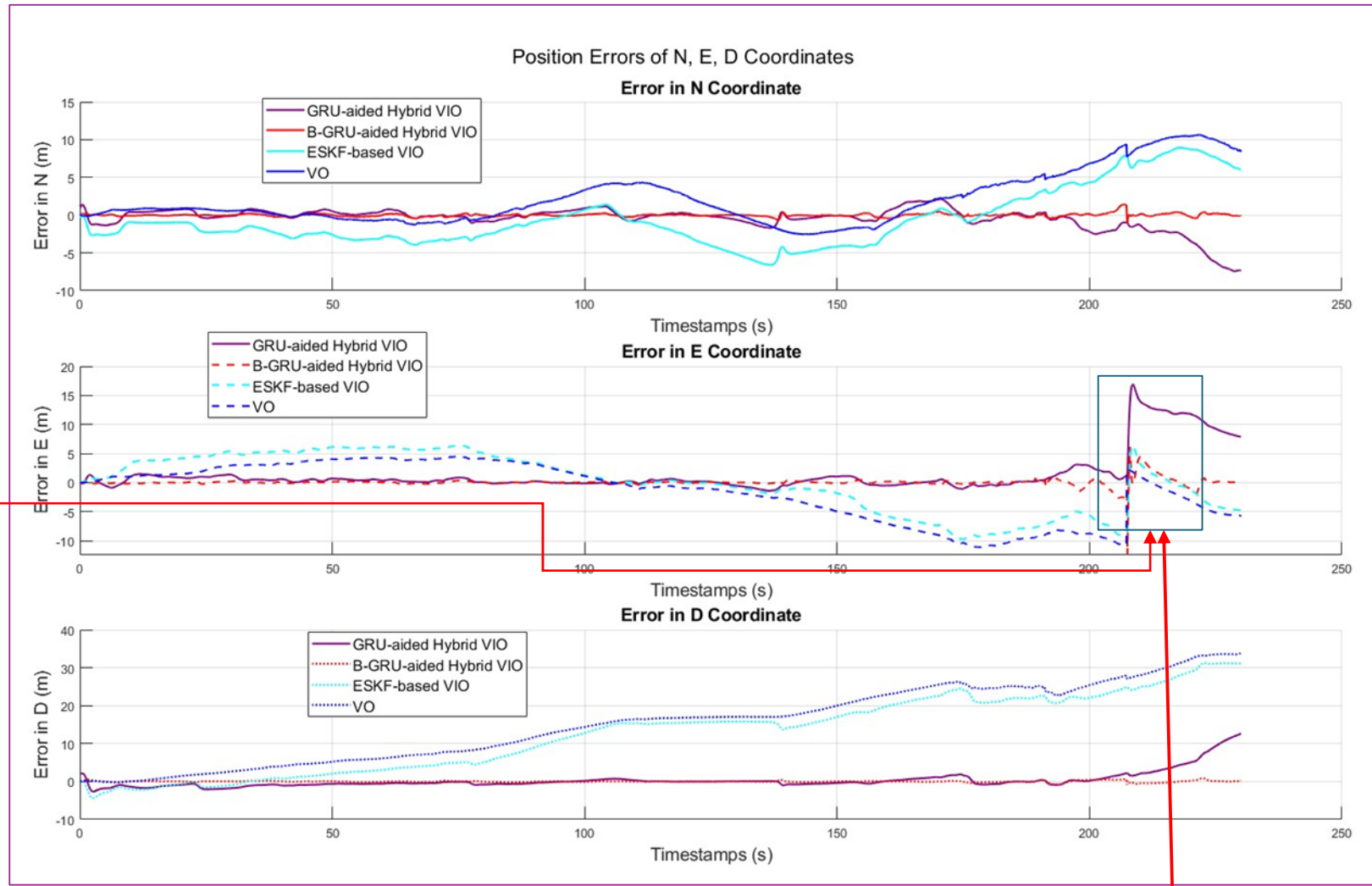
# Trajectory	Scenarios	Fault type (known)	
1	EuRoC MH05-difficult dataset	1. Rapid Motion 2. Dark environment 3. Shadows of objects 4. Texture-less environment 5. Mixture of lens blur	
2	Compound faults (incl. unseen environment) Sunny Weather Condition	Known faults	Unseen faults
		1. Turns with featureless walls. 2. Turns with sky-view. 3. Shadows of objects	1. Limited angular rotation 2. Altitude variation 3. Take-off with different altitudes.



Results (1)



Long tails has been minimized and performance improved under outlier effects



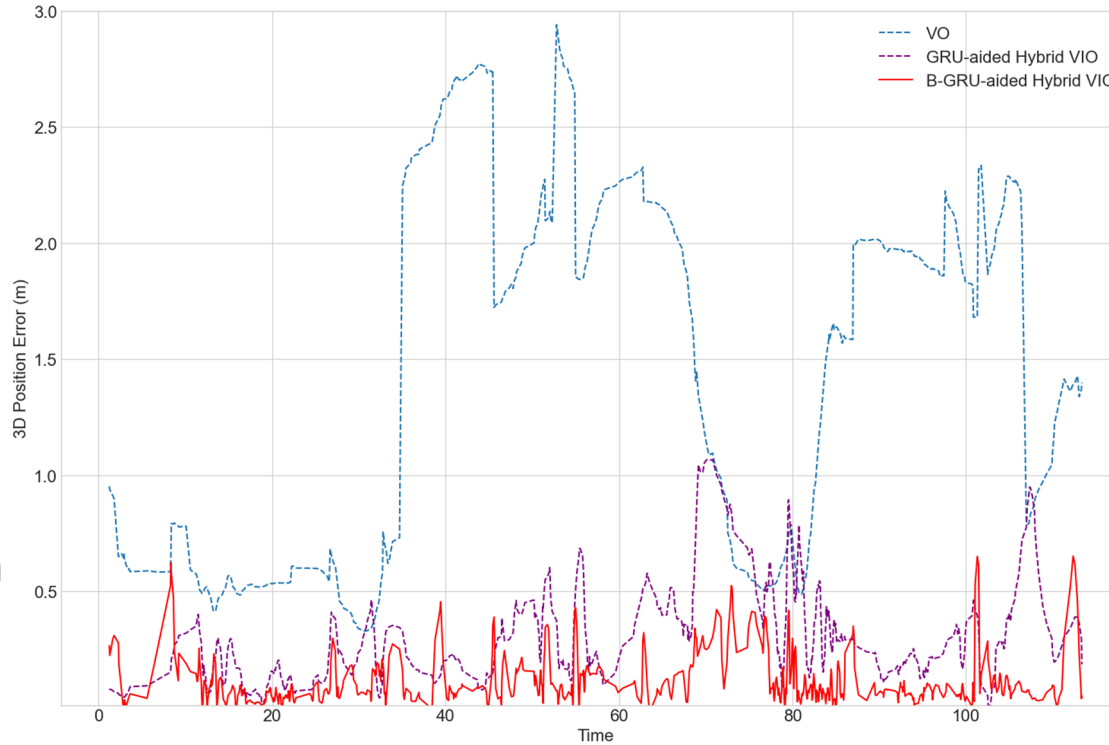
Techniques	RMSE (m)							95 th Percentile		
	N	E	V	3D PE	Horizontal PE	3D PE	Improvement	Horizontal PE (m)	Improvement	
VO	4.0	5.1	18.1	27.5	6.5	33.2	-	11.3	-	
ESKF-based VIO	3.7	4.8	16.0	24.1	6.1	29.6	40%	9.0	21%	
GRU-aided Hybrid VIO [11]	1.7	3.4	1.9	4.3	4.1	11.3	66%	12.1	-	
B-GRU-aided Hybrid VIO	1.3	0.6	0.9	3.1	1.4	3.7	88%	3.1	72%	

Due to rotation and periodic structure

Results (2)

VO struggles due to rotation in loop and high speed of 0.88 ms^{-1}

model adaptability in unseen complex environment

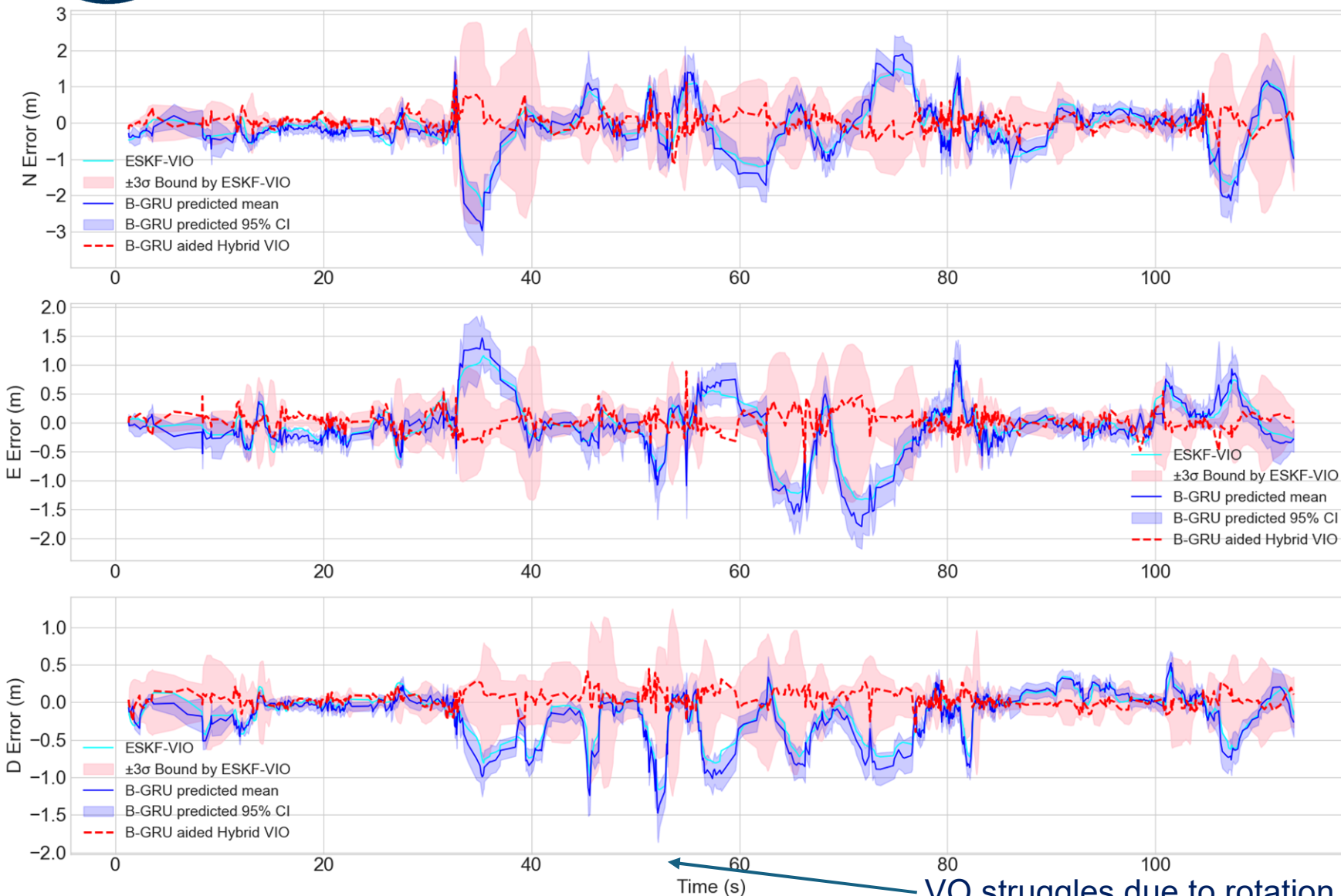


UAV rotates at 20s, 24.4s, 42.2s, 54.0s, 63.5s, 72.3s, 92s, 101s

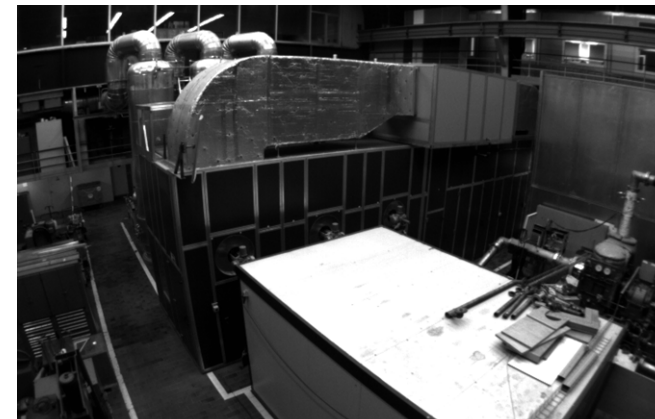
Aleatoric and epistemic uncertainty grow due to darkness, motion blur and lower feature availability

Techniques	RMSE (m)				Horizontal RMSE (m)	3D 95 th Percentile (m)
	N	E	V	3D	3D	
End-to-End VIO [4]	-	-	-	1.96	-	-
DeepVIO [14]	-	-	-	0.52	-	-
Self-VIO[3]	-	-	-	0.29*	-	-
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

- Simulated datasets were used for training of the B-GRU model
- Tested on unseen environment



Complex conditions- darkness,
featureless environment



Techniques	3 σ (OR%)			3 σ (OR%)
	N	E	V	3D
UA-VO [7]				21.9
ESKF-VIO	35.5	39.4	29.2	-
B-GRU-aided Hybrid VIO	16.0	17.9	17.6	-

UAV rotates at 20s, 24.4s, 42.2s, 54.0s, 63.5s, 72.3s, 92s, 101s

VO struggles due to rotation in loop and high speed of 0.88 ms^{-1}

- This study demonstrates performance enhancement using an enhanced hybrid VIO fusion framework with B-GRU-based measurement error prediction and correction with error boundaries estimation.
- Uncertainty reduction arises from the quality of extracted features, as well as darkness, motion blur, low-texture environment, and flight dynamics. Improvement achieved is over showed improvement in 33.8% compared to GRU-aided hybrid VIO and 78.06% compared to SOTA hybrid VIO in an unseen environment. (EuRoC dataset)
- 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 PE, providing error boundary in complex cases (EuRoC dataset).
- Outlier effects highlight the impact of aleatoric uncertainty and model mismatch in dynamic scenarios in trajectory 2 has been mitigated with a 64% improvement over GRU-aided hybrid VIO.
- Able to generalise under unseen scenarios and fault conditions; however, it requires external mitigation for dealing with sensor uncertainty reduction and outlier mitigation.
- Future studies will aim to further enhance architecture by adding more sensors and evaluating on real data from the flying drone.