Feature-Based Perception-Aware Multi-UAV Trajectory Planning

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Goal: Enhance vision-based state estimation in multi-UAV systems by exploiting visual feature information during trajectory planning to maintain reliable localization.

Approach: (a) Fisher information-based trajectory evaluation to favor motion that improves expected localization accuracy.

(b) Feature map-based frame alignment to correct relative vision drift and maintain a consistent shared map among agents.

(c) A decentralized planning framework that incorporates both individual feature visibility and covisible landmarks when selecting trajectories.

Motivation

- **VIO drift accumulates over time** due to IMU noise and imperfect feature tracking, leading to degraded localization in long-duration operations.
- Feature visibility is highly uneven in realistic environments; entering **feature-sparse regions** can quickly lead to estimator degradation or failure.
- **Covisible features** observed across agents provide **strong geometric constraints** that can be exploited to correct relative drift and maintain a consistent shared map.

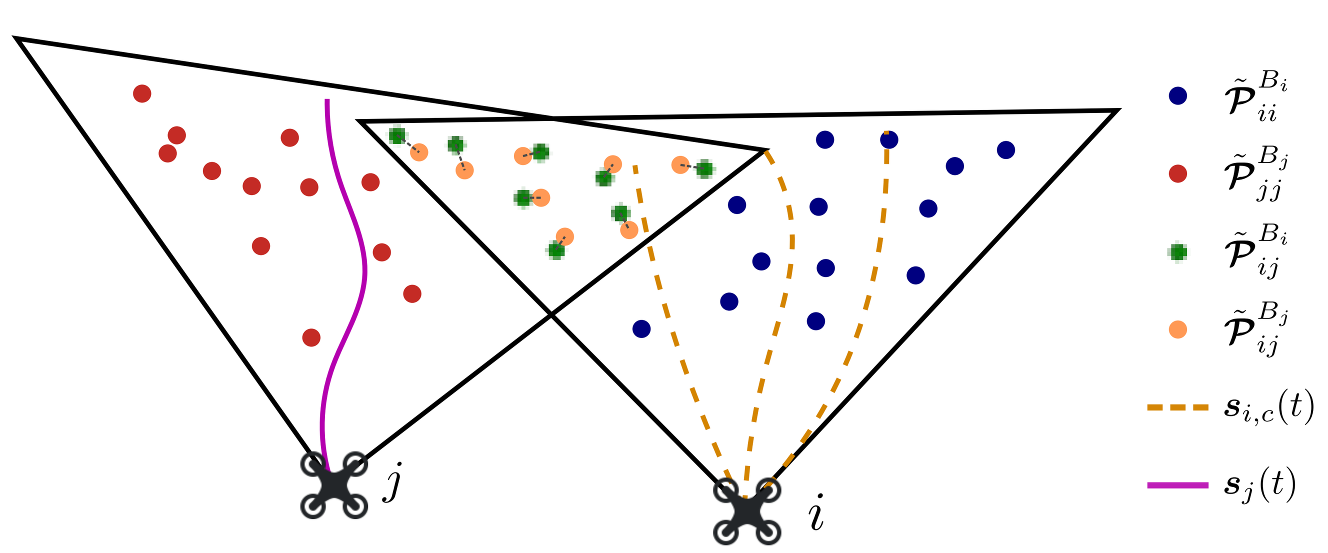
Problem Setup

- Each UAV runs VIO and maintains its own local 3D feature map, which can be shared at communication times.
- Feature-based map alignment fuses shared landmarks to maintain a consistent relative pose across agents.
- The planner selects a trajectory that **advances toward the goal** while **improving expected localization quality**.
- Trajectories are evaluated using a combined reward while ensuring the trajectory is **collision-free** and **dynamically feasible** and is chosen via sampling-based real-time optimization [1].

$$\underset{\text{Trajectory } \Gamma_i(t)}{\arg\max} \; k_{\text{goal}} \overbrace{R_{\text{goal},i}}^{\text{Progress Reward}} + k_{\text{perc}} \overbrace{R_{\text{perc},i}}^{\text{Perception Reward}}$$

$$\text{s.t.} \quad s_i(t) \in \mathcal{X}_{\text{free}}, \quad \forall t \in [0,T] \quad \text{Collision-free}$$

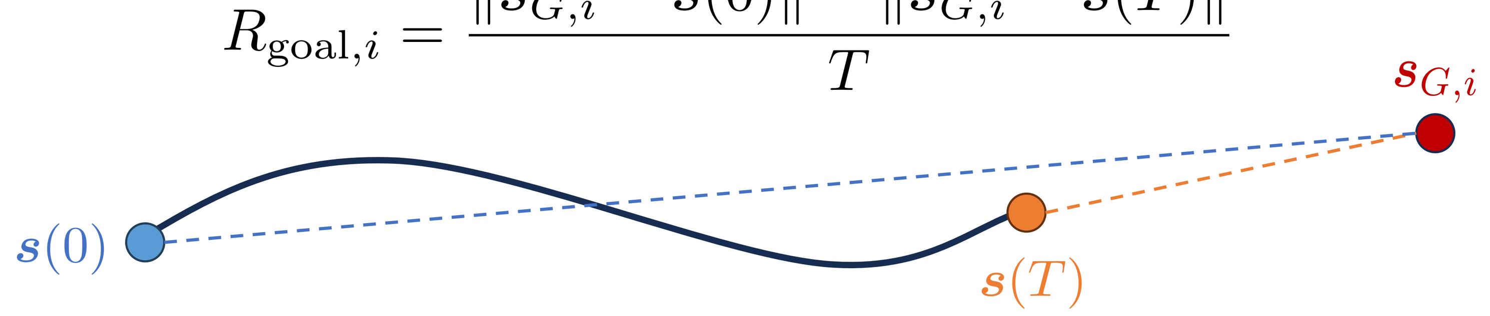
$$f_i(t), \omega_i(t) \in \mathcal{U}_{\text{feasible}}, \quad \forall t \in [0,T] \quad \text{Input-feasible}$$



Progress Reward

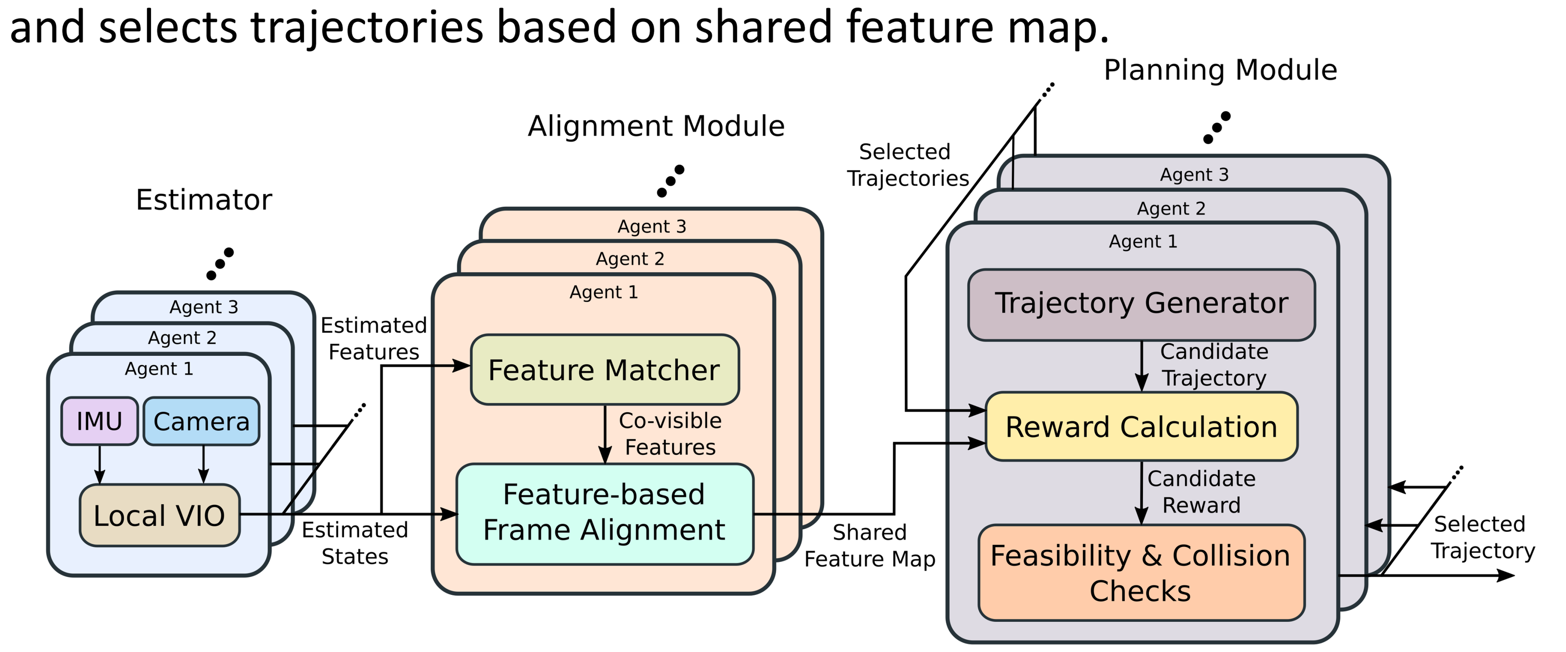
- The goal progress reward encourages the agent to reduce its distance to the target as efficiently as possible.

$$R_{\text{goal},i} = \frac{\|s_{G,i} - s(0)\| - \|s_{G,i} - s(T)\|}{T}$$



System Architecture

- Each agent runs a local VIO estimator to generate states and visual features.
- Agents periodically exchange local maps and align covisible features to form a consistent shared feature map.
- The planner samples trajectory candidates, evaluates a combined reward, and selects trajectories based on shared feature map.



Frame Alignment

- Fuse feature observations from multiple UAVs into a **shared feature map** in the **consensus world frame** to mitigate independent VIO drift.
- Use **pairwise covisible features** to jointly refine agent poses and shared landmarks via nonlinear least-squares optimization.

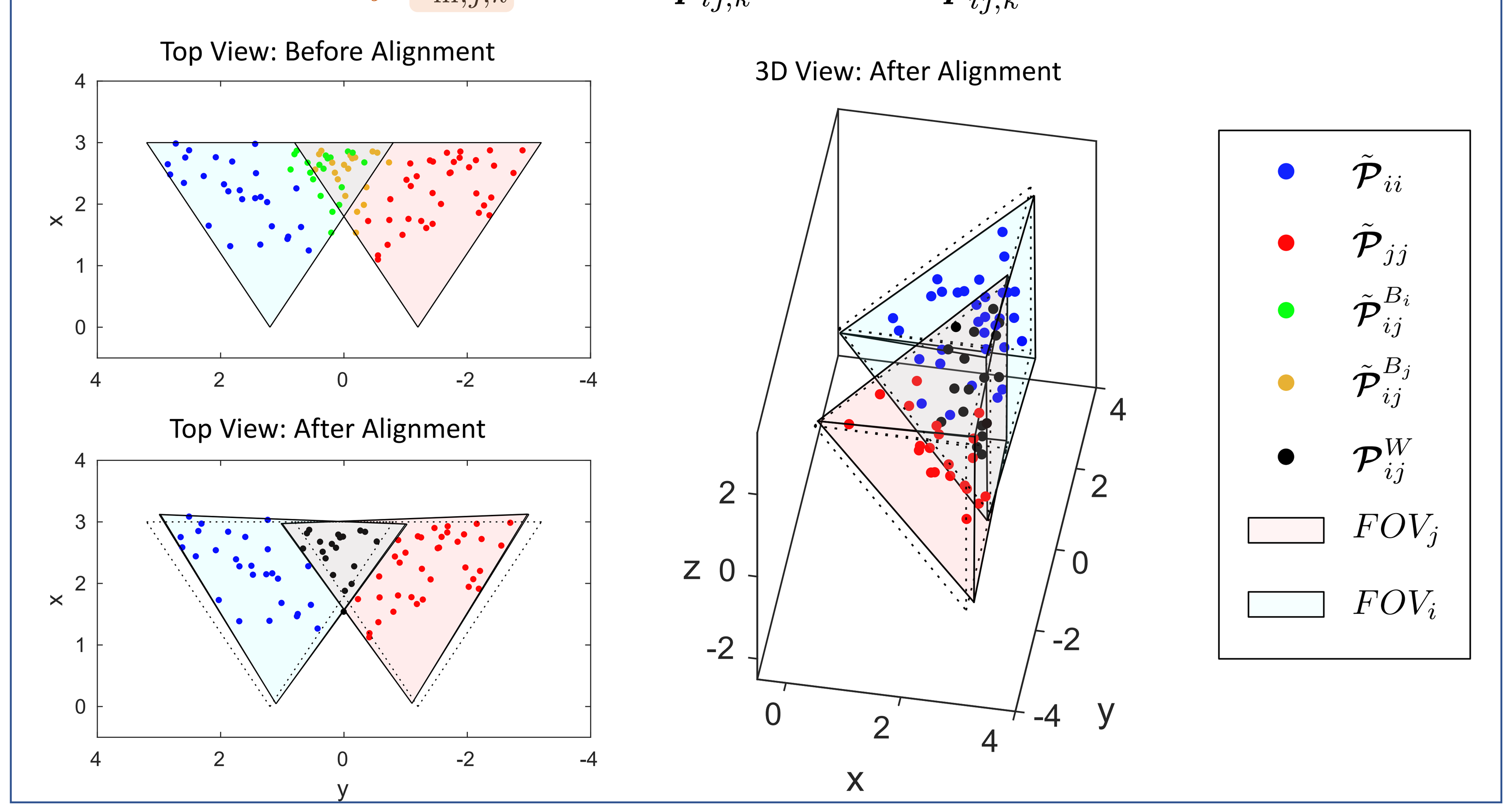
$$\min_{\Theta} \sum_{i \in \mathcal{V}} \|r_{\text{p},i}\|^2_{\Sigma^{-1}_{\text{p},i}} + \sum_{(i,j)\in\mathcal{E}} \sum_{k=1}^{m_{ij}} \left(\|r_{\text{m},i,k}\|^2_{\Sigma^{-1}_{\text{m},i}} + \|r_{\text{m},j,k}\|^2_{\Sigma^{-1}_{\text{m},j}} \right)$$

Decision Variable: $\Theta = \overbrace{\{\xi_i\}_{i\in\mathcal{V}}}^{\text{Pose Error}} \cup \overbrace{\{\mathcal{P}^W_{ij,k}\}_{(i,j)\in\mathcal{E},\, k=1..m_{ij}}}^{\text{Shared Feature Positions}}$

Prior Residual: $r_{\text{p},i} = \xi_i$

Meas. Residual for i: $r_{\text{m},i,k} = R^{B_iW} p^W_{ij,k} + t^{B_iW} - \tilde{p}^{B_i}_{ij,k}$

Meas. Residual for j: $r_{\text{m},j,k} = R^{B_jW} p^W_{ij,k} + t^{B_jW} - \tilde{p}^{B_j}_{ij,k}$



Information-Based Perception-Aware Reward

- Use a **Fisher information-based metric** to evaluate the expected information gain along each candidate trajectory.
- **Prior information** is constructed following [2], representing the contribution from independent VIO feature tracks.
- **Shared measurement information** is derived from the frame alignment least-squares formulation, capturing inter-agent covisibility.
- A **perception-aware reward** is computed using the D-optimality criterion.

$$\underbrace{\Lambda_{\text{meas},i,\tau,k}}_{\text{Measurement Information}} = J^{p\,\top}_{\xi_i,k} \, \Sigma^{-1}_{\text{m},i} \, J^p_{\xi_i,k} \qquad J^p_{\xi_i,k} := \left. \frac{\partial p^{B_i}_{ij,k}}{\partial \xi_i} \right|_{\xi_i=0}$$

$$\underbrace{\Lambda_{i,\tau}}_{\text{Information at sampled pose}} = \underbrace{\Lambda_{\text{prior},i,\tau}}_{\text{From [2]}} + \Lambda_{\text{meas},i,\tau} \qquad R_{\text{perc},i} = \frac{1}{n_{\text{poses}}} \sum_{\tau=1}^{n_{\text{poses}}} \log\det(\Lambda_{i,\tau})$$

Results

- Two UAVs hovered with injected translational drift (0.5 m) to test the alignment module. The correction reduced inter-agent distance error by **~60%.**

Drift Direction	RMSE Old (m)	RMSE New (m)	% Reduction
X	0.510	**0.212**	58.3
Y	0.165	**0.058**	65.0
Z	0.219	**0.082**	62.7

- Simulations of two UAVs planning in three environments compared perception-aware and baseline methods. The proposed planner consistently **increased visible and shared features**, enhancing observability while maintaining **comparable goal accuracy**.

Case	Method	# Visible	# Covisible	Error A	Error B
1	perception-agnostic	149	18	**0.52**	0.56
	perception-aware	**169**	**30**	0.80	0.56
2	perception-agnostic	132	0	**0.23**	**0.24**
	perception-aware	**141**	0	0.39	0.50
3	perception-agnostic	43	3	1.07	1.06
	perception-aware	**72**	**8**	**0.96**	**1.01**

References

1. N. Bucki, J. Lee, and M. W. Mueller, "Rectangular pyramid partitioning using integrated depth sensors (RAPPIDS): A fast planner for multicopter navigation," IEEE Robotics and Automation Letters, vol. 5, no. 3, pp. 4626–4633, 2020.
2. X. Wu, S. Chen, K. Sreenath, and M. W. Mueller, "Perception-aware receding horizon trajectory planning for multicopters with visual-inertial odometry", IEEE Access, Vol 10, pp. 87911-87922, 2022.