High-Performance and Energy-Saving Autonomous Navigation System for Aerial-Ground Robots

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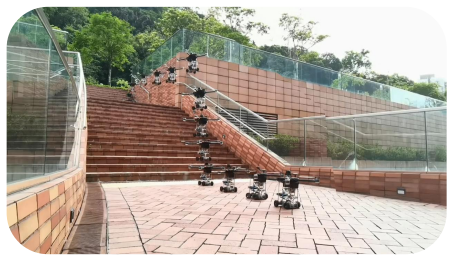
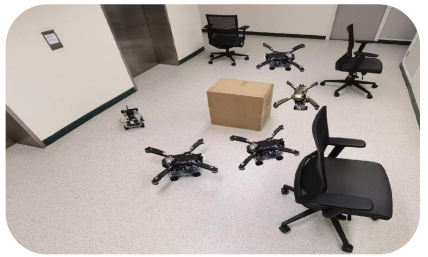
Supervisor : Prof.Heming Cui

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Traditional Mobile Robots

Husky UGV

Agilex Robotics

DJI M350 RTK

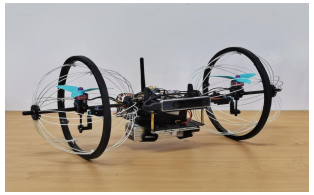
Meituan Robotics

Aerial-Ground Robots (AGRs) is Coming !

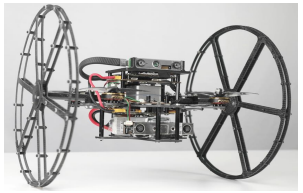
(Transcending Limitations of Traditional Robots)

Academia

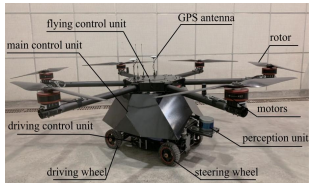
Nature Communications'23



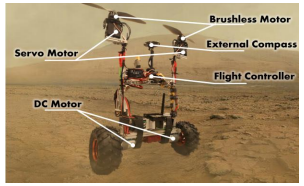
RA-L'22



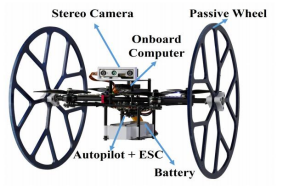
RA-L'22



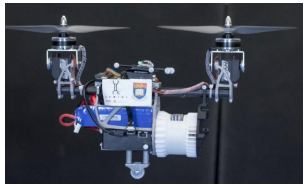
T-Mech'21



IROS'23



IROS'23



IROS'22

AIM'23

Industry

AFWERX

Pegasus III

Xiaopeng Huitian X1

Xiaopeng Huitian X2

Jetson One

Pal-V

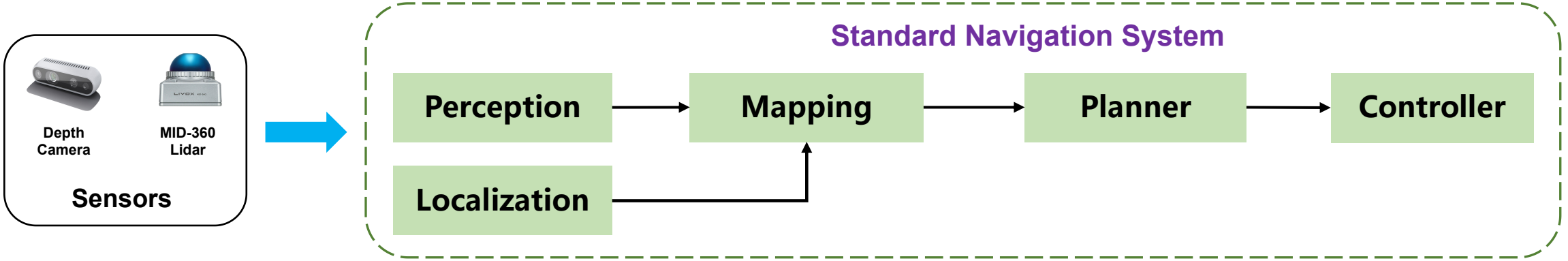
Aska

SkyDrive

Limitations of Traditional UAVs and UGVs Necessitating Aerial-Ground Robotic Systems:

- **Limited mobility:** UAVs can only fly, while UGVs are restricted to ground movement.
- **Short endurance:** UAVs have limited flight time, and UGVs consume high energy in complex environments.
- **Constrained workspace:** UAVs operate primarily in the air, while UGVs are limited to the ground.
- **Poor environmental adaptability:** UAVs struggle in adverse weather or complex environments, and UGVs face challenges in extreme terrains.

■ *Autonomous Navigation in Complex Environments is Very Important For AGRs*



■ *Challenges in Achieving <u>High-performance</u> and <u>Energy-efficient</u> Autonomous Navigation*

Challenge 1 - Limitations of the ***Perception Module***:

- The sensor's limited field of view obstructs the perception of obstacle distribution behind occlusions, resulting in an incomplete local map with unknown and occluded areas.

Challenge 2 - Limitations of the ***Path Planner***:

- Existing planners fail to address AGR-specific requirements, particularly energy efficiency and dynamic constraints. AGRs' inherent non-holonomic constraints make directly migrating and using UAV planners impractical.

Challenge 3 - Prediction Result ***Update***:

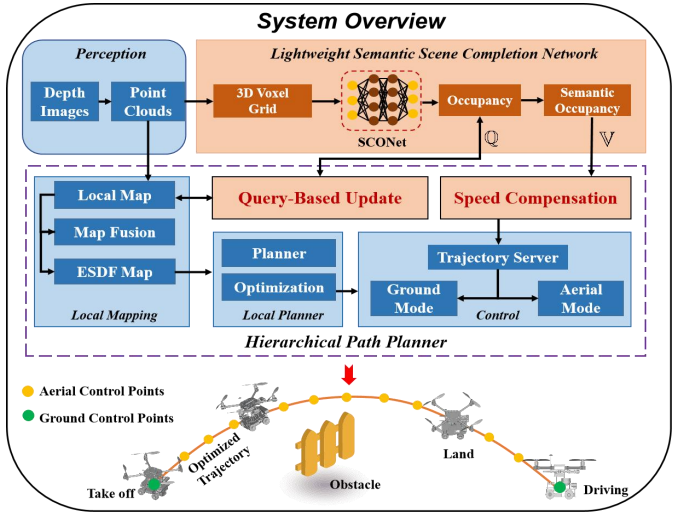
- While a new 3D semantic occupancy network can predict obstacle distribution in occluded areas, exploring low-latency methods to update these predictions into the local map remains challenging.

Outline: High-Performance and Energy-Saving Autonomous Navigation System for Aerial-Ground Robots

- **Basic idea:** By proposing **a novel perception network** and **a path planner** tailored specifically for Aerial-Ground Robots (AGRs), we can address all three challenges posed by existing works and achieve an optimal trade-off between **performance and efficiency** in two distinct navigation systems:

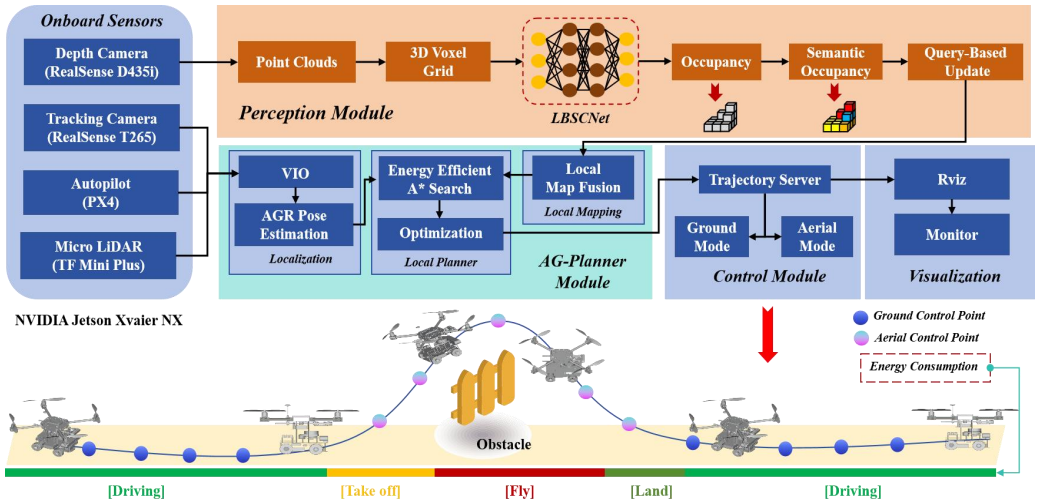
1. AGRNav: Efficient and Energy-Saving Autonomous Navigation for Air-Ground Robots in Occlusion-Prone Environments

2. HE-Nav: A High-Performance and Efficient Navigation System for Aerial-Ground Robots in Cluttered Environments



AGRNav

The First AGR-Tailored Occlusion-Aware Navigation System



HE-Nav

The First AGR-Tailored ESDF-Free Navigation System

AGRNav: Efficient and Energy-Saving Autonomous Navigation for Air-Ground Robots in Occlusion-Prone Environments

Background

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➢ **AGR combines the advantages of unmanned ground vehicle (UGV) and unmanned aerial vehicles (UAV).**

UGV

Advantages:
- ✓ long endurance
- ✓ low energy consumption

Disadvantages:
- ◆ Limited field of view
- ◆ Low velocity

UAV

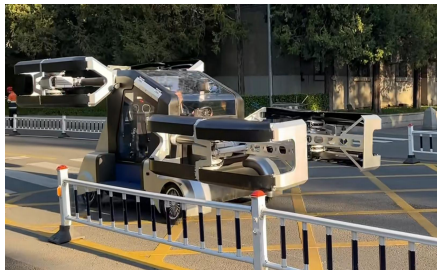
Advantages:
- ✓ High mobility
- ✓ Fast velocity
- ✓ Wide field-of-view

Disadvantages:
- ◆ High energy consumption
- ◆ Low load capacity

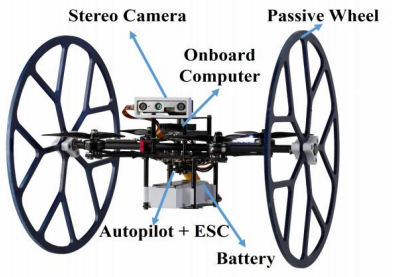
➢ **Air-ground robots (AGRs)**, which are known for their ***outstanding mobility*** and ***long endurance***, have been gaining significant interest lately and show great potential for applications in search and rescue tasks.

Nature Communications'2023 **[1]**

RAL'2022 **[2]**



T-Mech'2021 **[3]**



RAL'2022 **[4]**

[1] Sihite E, Kalantari A, Nemovi R, et al. Multi-Modal Mobility Morphobot (M4) with appendage repurposing for locomotion plasticity enhancement[J]. Nature communications, 2023, 14(1): 3323.

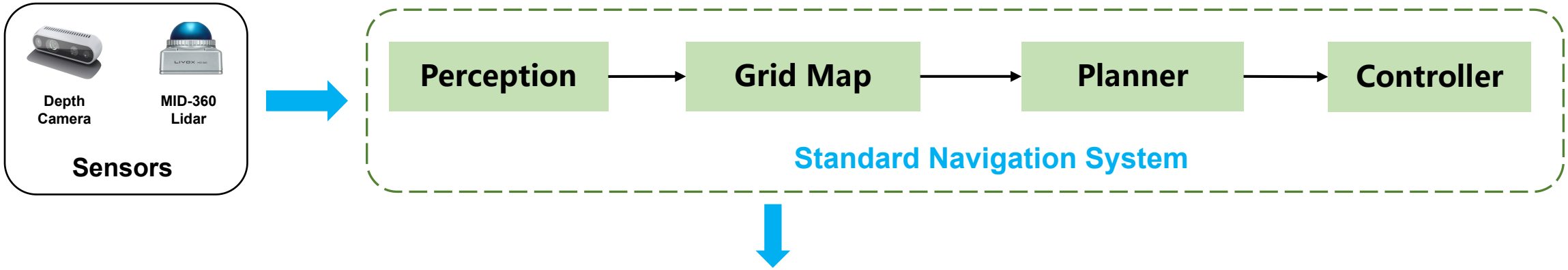
[2] Yang J, Zhu Y, Zhang L, et al. SytaB: A class of smooth-transition hybrid terrestrial/aerial bicopters[J]. IEEE Robotics and Automation Letters, 2022, 7(4): 9199-9206.

[3] Tan Q, Zhang X, Liu H, et al. Multimodal dynamics analysis and control for amphibious fly-drive vehicle[J]. IEEE/ASME Transactions on Mechatronics, 2021, 26(2): 621-632.

[4] Zhang R, Wu Y, Zhang L, et al. Autonomous and adaptive navigation for terrestrial-aerial bimodal vehicles[J]. IEEE Robotics and Automation Letters, 2022, 7(2): 3008-3015.

Requirements

- To achieve ***collision-free*** autonomous navigation, the ***perception***, ***planning***, and ***control*** modules within a standard robot navigation system are deployed on the onboard computer (i.e., NVIDIA Jetson Xavier NX) and run asynchronously.



- ***An ideal AGR navigation system needs to meet the following requirements*:**

Efficient

- **Planning Success Rate**: No collision occurs during movement from the starting point to the endpoint.
- **Moving Time**: The movement time from the starting point to the endpoint is short.

Energy-saving

- **Energy Consumption**: Minimal power consumption during navigation.
- **Mode Switching:** Switch to flight mode only when encountering insurmountable obstacles.

Challenge

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Existing AGR Navigation Systems Cannot Meet all Requirements

- Existing robot navigation systems include ***Mapping-Based*** methods and ***Learning-Based*** methods.
- **Mapping-Based Methods (e.g., TABV [RAL' 2022]; HDF [IROS' 2019])**

- ***How it works***

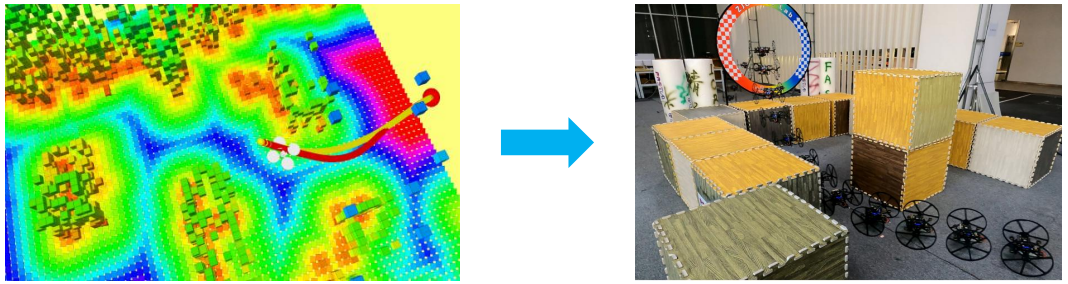
① Perceive surrounding obstacles and build an **occupany grid map**.

② Construct Euclidean Signed Distance Field **(ESDF) map**.

③ A path planner based on the **A* algorithm** searches for trajectories.

④ Tracking the trajectory using the PX4 controller.

Mapping-Based Method



- ***Advantages:*** **High** navigation **success rate** in simple and unobstructed scenarios.
- ***Limitations:*** **High collision risk** and **suboptimal energy consumption** in occluded and unknown scenarios.

Inefficient

Redundant ground trajectories and flight trajectories result in additional energy consumption

Challenge

➢ **Learning-Based Methods, only designed for ground robots (e.g., OPNet [IROS' 2021])**

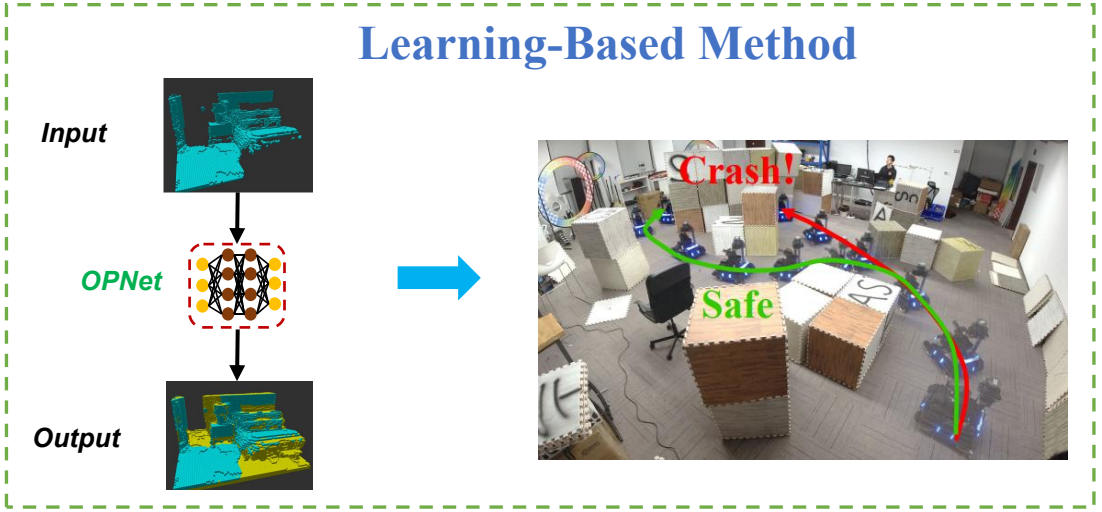
- ***How it works***

① Perceive surrounding obstacles and build an **original grid map**.

② Use **OPNet** to predict obstacle distribution in occluded areas.

③ **Fusion** of predicted local map and original local map.

④ Path planner planning trajectory.



- ***Advantages:*** Predict the distribution of obstacles in blocked areas in advance to **improve** planning success rate.
- ***Limitations:***
  - The prediction **accuracy** is **low.**
  - The map update **delay** **is** **high**.

Our Question and Observation

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Can we address the limitations in *mapping-based* and *learning-based* methods to create an AGR navigation system that is both highly efficient and energy-saving?

- A ***lightweight semantic completion network*** is proposed to predict the distribution of obstacles in occlusion areas in real time.
  - ✓ Depthwise separable convolution;
  - ✓ self-attention mechanism;
- A ***novel update strategy*** is proposed to avoid high-latency occupancy updates (e.g., directly merging two maps).
  - ✓ Query-based method;
- A ***hierarchical path planner*** is proposed to search energy-efficient, safe, smooth and dynamically feasible air-ground hybrid paths.

Methods	Category	Efficiency Metrics		Energy Metric	Additional Network Inference Metrics		Suitable for AGRs
		Planning Success Rate	Moving Time	Energy Consumption	Prediction Accuracy	Real-Time Inference	
HDF [IROS'19]	Mapping-Based	☹	☹	☹	None	None	√
TABV [RAL'22]	Mapping-Based	☹	☹	☺	None	None	√
OPNet [IROS'21]	Learning-Based	None	None	None	☹	☹	x
AGRNav (Ours)	**Prediction-Based**	☺	☺	☺	☺	☺	√

ARGNav: Efficient and Energy-Saving

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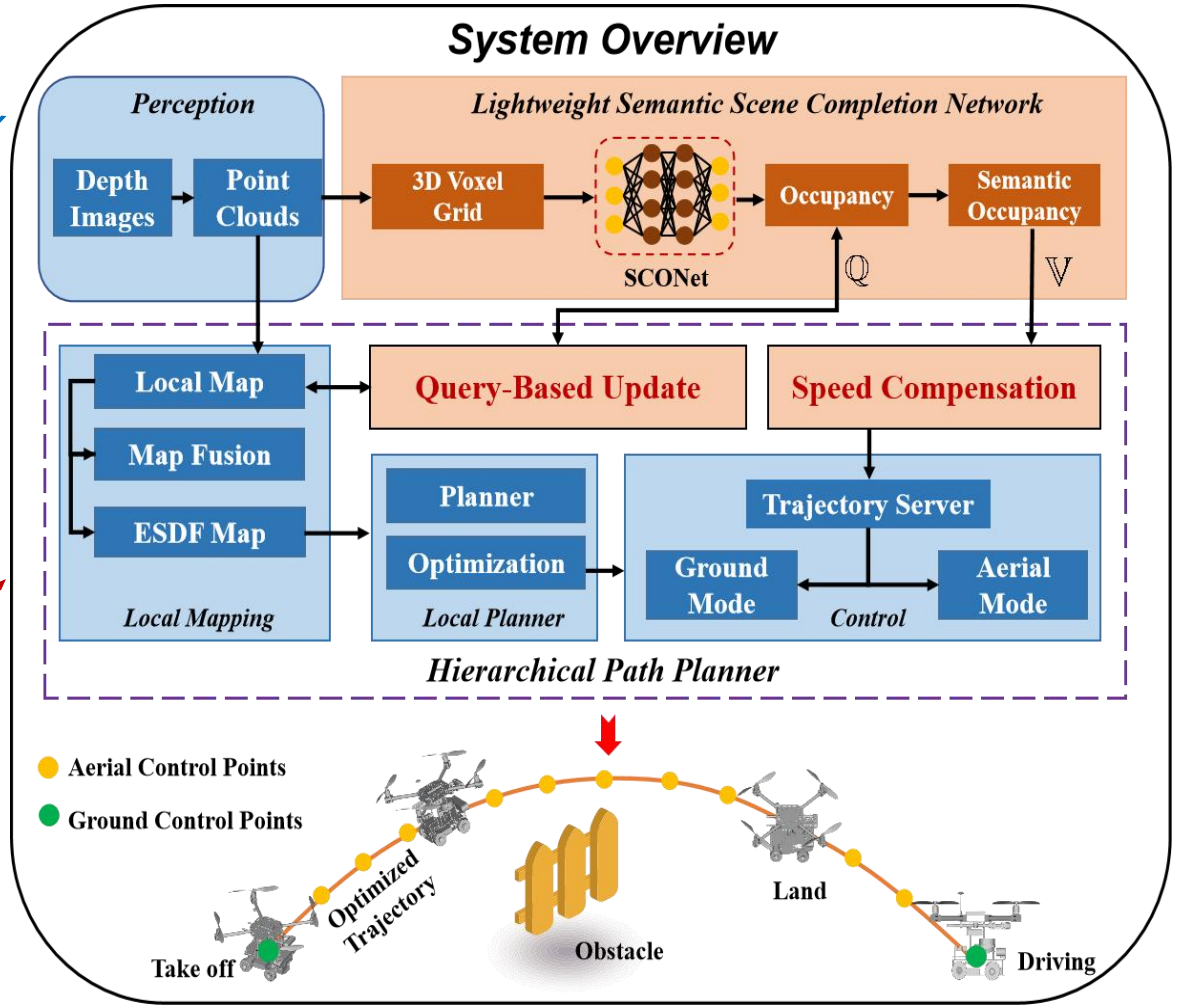
◆ The Overview of Our Proposed System: AGRNav.

ESDF-Based Planner

(i) a Kinodynamic A* path searching front-end,
(ii) an ESDF-based trajectory optimization back-end.
(iii) a post-refinement procedure.

Mode Switching

- When the z-axis coordinate of the next control point is greater than the ground threshold, that is, when mode switching is required, an additional trigger signal will be sent to the controller (i.e., PX4 Autopilot).



SCONet

- To enable SCONet to capture rich and dense contextual information as well as features of occlusion areas, it integrates two self-attention mechanisms.

Query-based Update Strategy

- After mapping, only the occupancy status of free voxels is queried and updated instead of fusing the predicted map and the original map to ensure low latency.

Contribution ①

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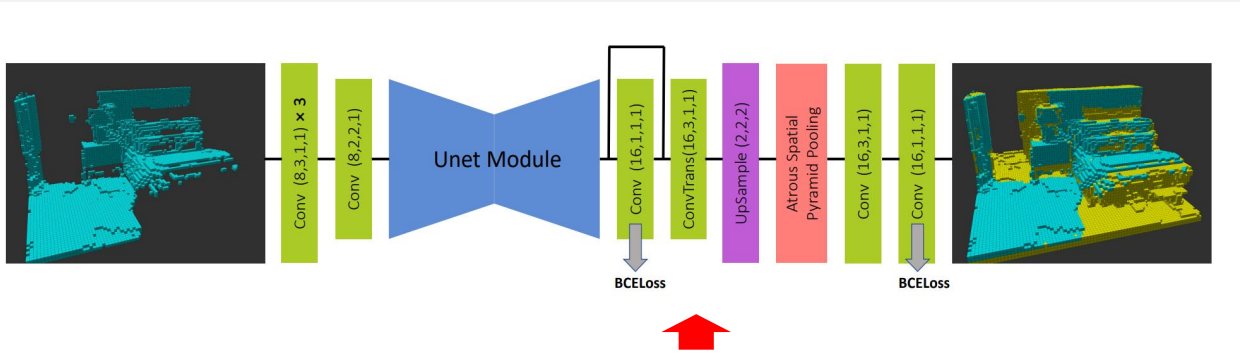
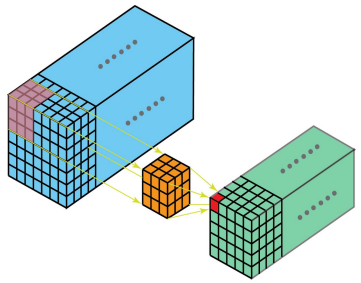
A Lightweight Semantic Scene Completion Network (SCONet)



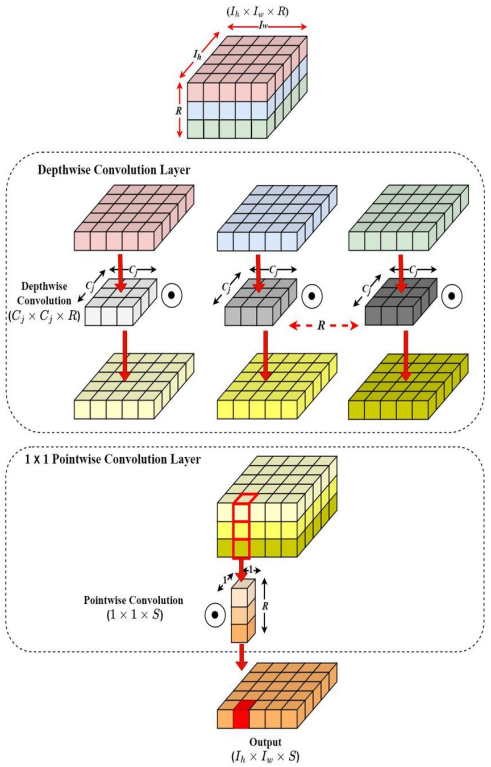
Network Limitation:

- Computationally intensive 3D convolution
- High latency update strategy
- Unable to capture fine-grained features

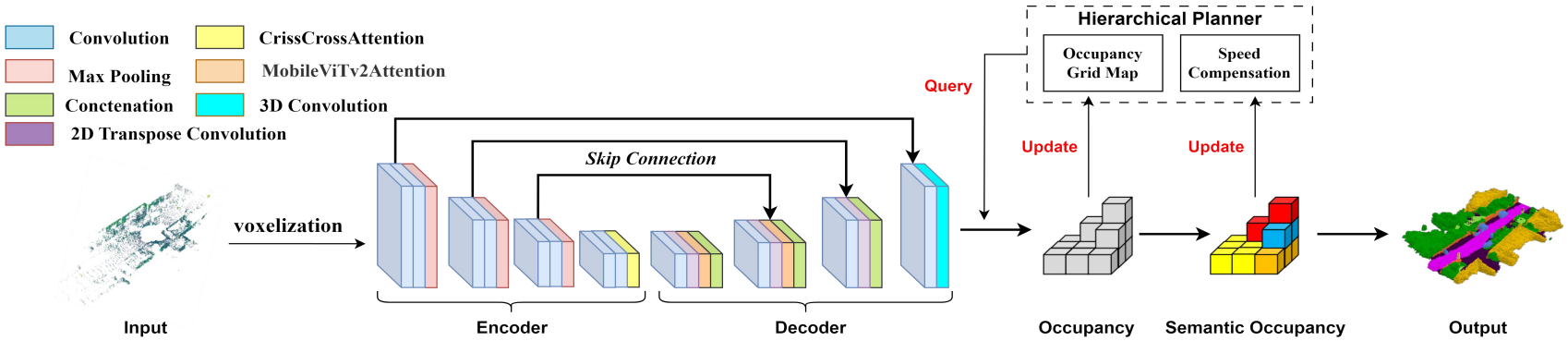
Standard Convolution



Depthwise Separable Convolution



- **Fewer Parameters**
- **Faster Speed**
- **Easier to port**
- **More Streamlined**



Contribution ①

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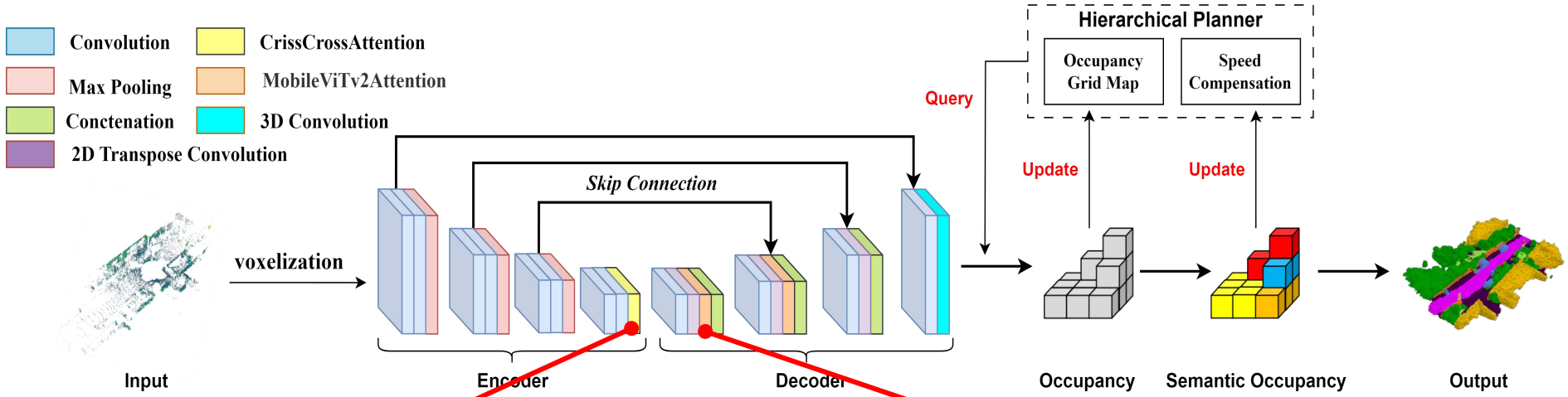
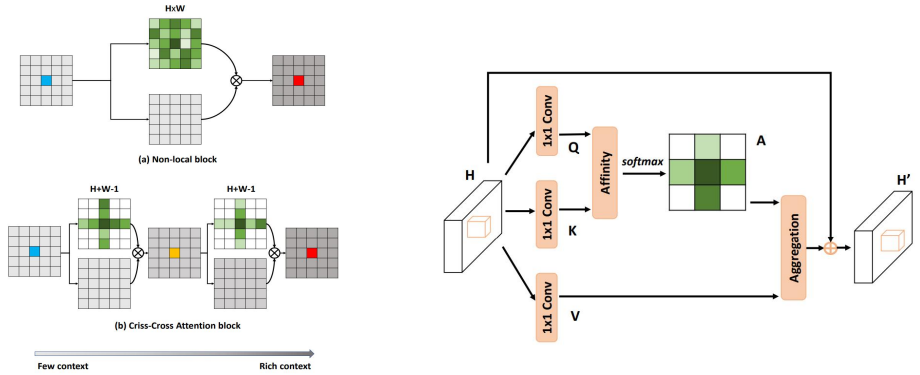
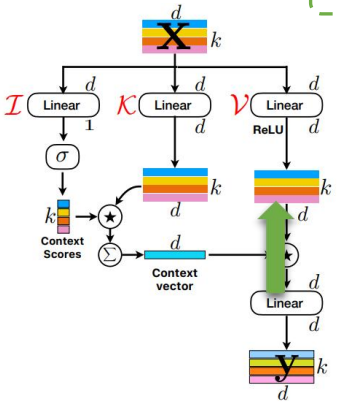


Criss-Cross Attention (CCA)



MobileViT-v2 Attention

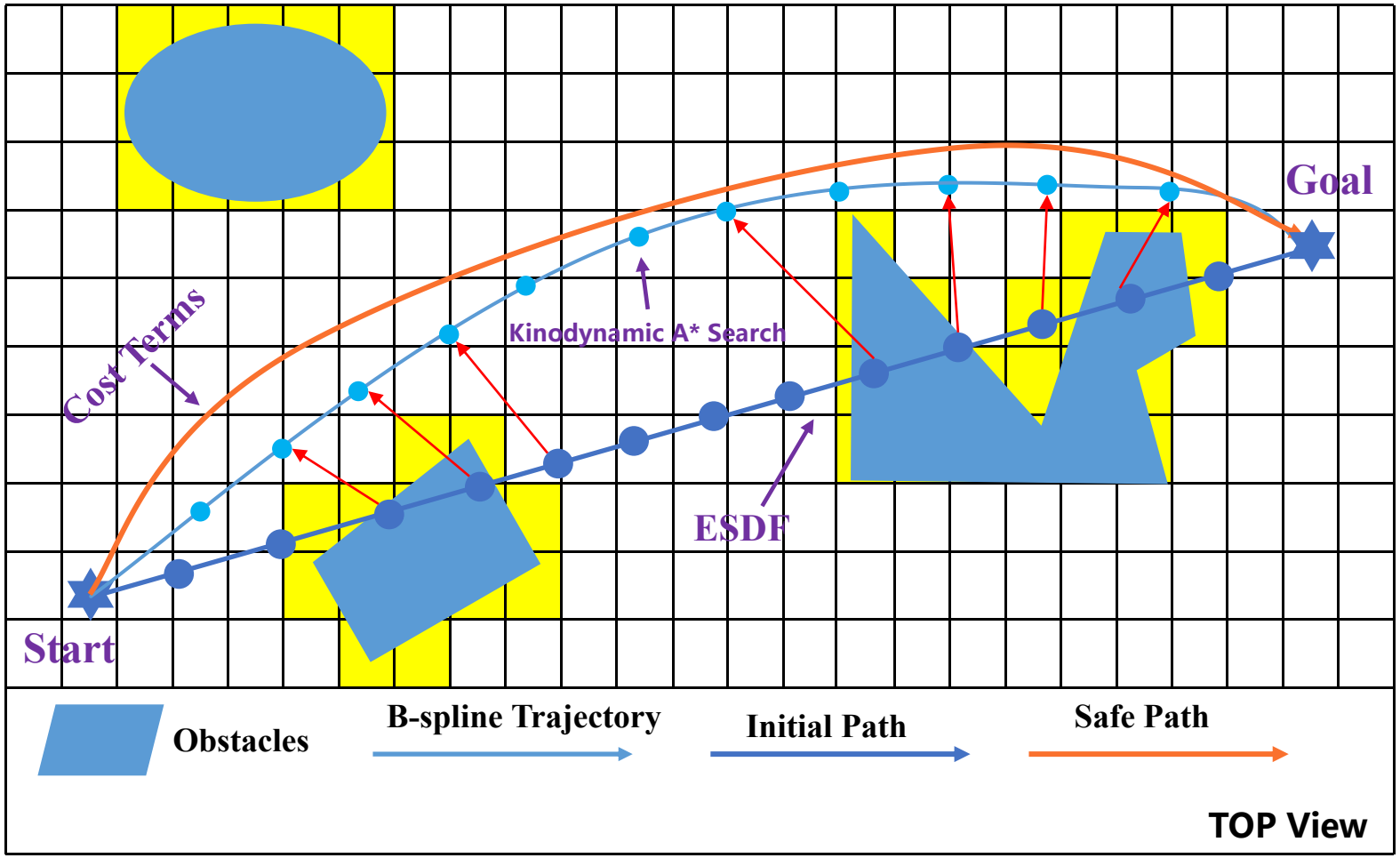


$$\mathbf{y} = \left(\underbrace{\sum \left(\overbrace{\sigma\left(\mathbf{x}\mathbf{W}_\mathbf{I}\right)}^{\mathbf{c}_\mathbf{s} \in \mathbb{R}^k} * \mathbf{x}\mathbf{W}_\mathbf{K} \right)}_{\mathbf{c}_\mathbf{v} \in \mathbb{R}^d} * \mathrm{ReLU}\left(\mathbf{x}\mathbf{W}_\mathbf{V}\right) \right) \mathbf{W}_\mathbf{O}$$

★ Broadcasted element-wise multiplication σ Softmax Σ Element-wise sum • Dot-product || Concatenation

Contribution ②

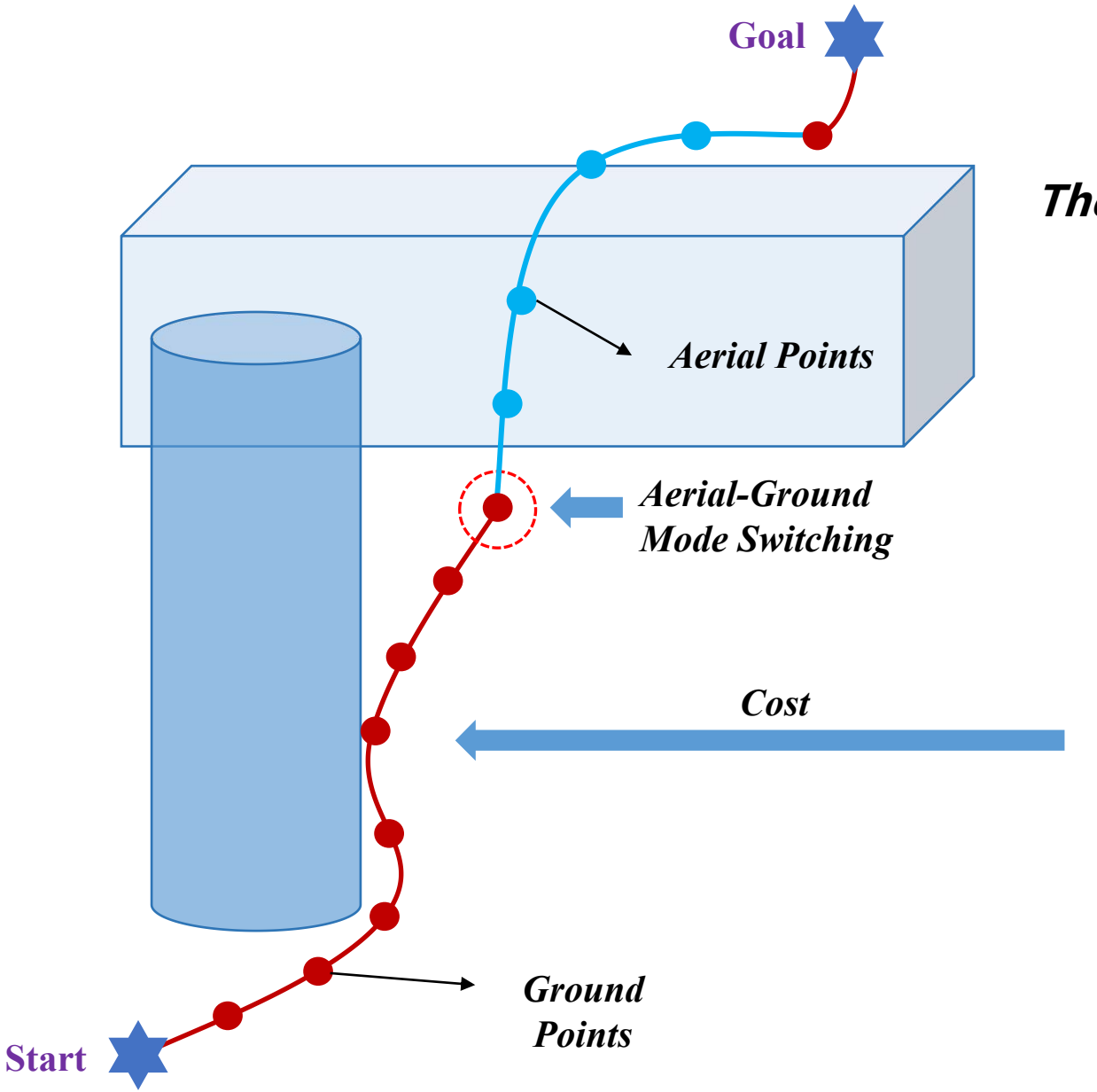
A Hierarchical ESDF-Based Path Planner



Algorithm 1: Kinodynamic Path Searching

```
1  Initialize();
2  while ¬ P.empty() do
3      n_c ← P.pop(), C.insert(n_c) ;
4      if ReachGoal(n_c) ∨ AnalyticExpand(n_c) then
5          return RetrievePath();
6      primitives ← Expand(n_c);
7      nodes ← Prune(primitives);
8      for n_i in nodes do
9          if ¬ C.contain(n_i) ∧ CheckFeasible(n_i) then
10             g_temp ← n_c.g_c + EdgeCost(n_i) ;
11             if ¬ P.contain(n_i) then
12                 P.add(n_i);
13             else if g_temp ≥ n_i.g_c then
14                 continue;
15             n_i.parent ← n_c,  n_i.g_c ← g_temp;
16             n_i.f_c ← n_i.g_c + Heuristic(n_i);
```

Contribution ②



The overall objective function is formulated as follows:

$$f_{total} = \lambda_s f_s + \lambda_c f_c + \lambda_f (f_v + f_a) + \lambda_n f_n.$$

$$f_s = \sum_{i=p_b-1}^{N-p_b+1} \| \underbrace{(\mathbf{Q}_{i+1} - \mathbf{Q}_i)}_{\mathbf{F}_{i+1,i}} + \underbrace{(\mathbf{Q}_{i-1} - \mathbf{Q}_i)}_{\mathbf{F}_{i-1,i}} \|^2$$ ***Smoothness Cost***

$$f_n = \sum_{i=1}^{M-1} F_n(\mathbf{Q}_{ti})$$ ***Curvature Cost***

$$f_c = \sum_{i=p_b}^{N-p_b} F_c(d(\mathbf{Q}_i))$$ ***Collision Cost***

$$f_v = \sum_{\substack{\mu \in \\ \{x,y,z\}}} \sum_{i=p_b-1}^{N-p_b} F_v(V_{i\mu}), \quad f_a = \sum_{\substack{\mu \in \\ \{x,y,z\}}} \sum_{i=p_b-2}^{N-p_b} F_a(A_{i\mu})$$ ***Dynamical Feasibility Cost***

Implementation and Evaluation

◆ Implementation Details:

- **SCONet** was trained and tested on a server with 4 NVIDIA RTX 3090 GPUs using the SemanticKITTI dataset, achieving optimal map completion accuracy after 80 epochs of training with data augmentation and deployed offline.
- **AGRNav** is developed using C++ and packaged as a ROS package for deployment on the onboard computer (i.e., Jetson Xvaier NX).

◆ Baseline AGR Navigation Systems:

- HDF [IROS'2019]
- TABV [ICRA'2022]

◆ Evaluation settings:

- **Simulation Experiments** were executed on a laptop equipped with Ubuntu 20.04, an i9-13900HX CPU, and an NVIDIA RTX 4060 GPU to simulate aerial-ground robotic navigation within complex environments.

- We employed AGRNav on a custom AGR platform for **indoor and outdoor experiments**, using Prometheus software, with a RealSense D435i depth camera, a T265 tracking camera, and a Jetson Xavier NX computer.

Mode	Average Power	Time (mins)
Fly	987.61 W	14
Hover	532.07 W	26
Ground	197.52 W	55

Evaluation Questions

01

- How is AGRNav’s end-to-end navigation efficient compared to baselines ?

02

- How does the energy consumption of AGRNav compare to the baseline ?

03

- How does the prediction accuracy and real-time performance of key components SCONet compare to the baseline?

End-to-End Performance

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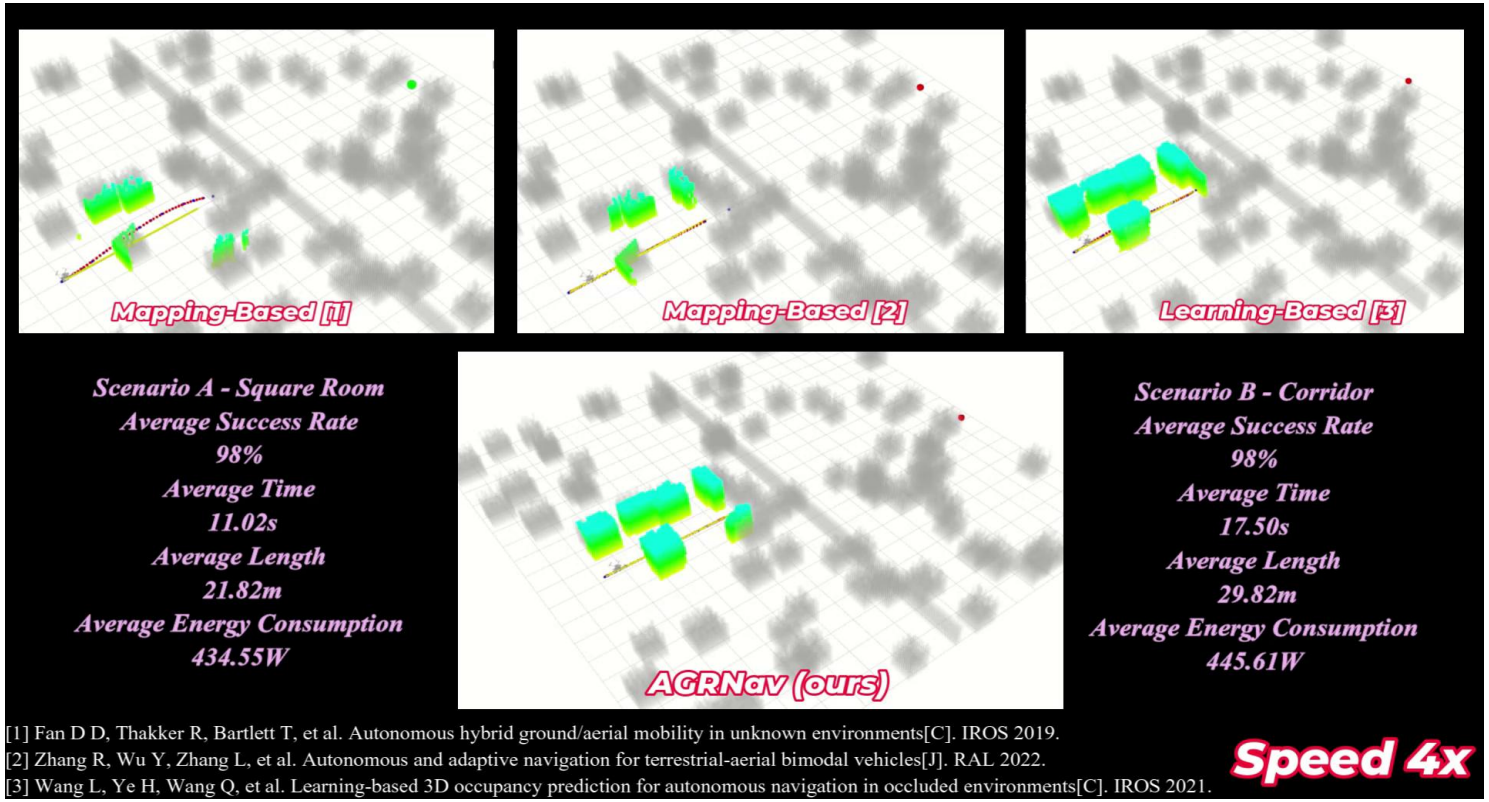
◆ Simulation Experiments:

Table 1

Mode	Average Power	Time (mins)
Fly	987.61 W	14
Hover	532.07 W	26
Ground	197.52 W	55

Table 2

Env.	Method	Succ. (%)	Time (s)	Leng. (m)	Power (W)
Square Room	Fan's [5]	85.0	13.13	33.79	919.07
	Zhang's [4]	95.0	12.05	23.09	793.30
	OPNet [12]	91.0	12.90	32.12	888.04
	AGRNav(Ours)	**98.0**	**11.02**	**21.82**	**434.55**
Corridor	Fan's [5]	88.0	21.24	33.10	565.24
	Zhang's [4]	97.0	**16.97**	30.69	519.20
	OPNet [12]	90.0	18.45	32.85	534.11
	AGRNav(Ours)	**98.0**	17.50	**29.82**	**445.61**



[1] Fan D D, Thakker R, Bartlett T, et al. Autonomous hybrid ground/aerial mobility in unknown environments[C]. IROS 2019.
[2] Zhang R, Wu Y, Zhang L, et al. Autonomous and adaptive navigation for terrestrial-aerial bimodal vehicles[J]. RAL 2022.
[3] Wang L, Ye H, Wang Q, et al. Learning-based 3D occupancy prediction for autonomous navigation in occluded environments[C]. IROS 2021.

- **Table 2 :** our AGRNav outperforms the other three approaches, achieving the **highest success rate (98%)**.
- **Table 2 :** our AGRNav substantially reduces redundant paths and cuts energy consumption by half (i.e., **average consumption per second is 434.55 W**) in a square room.
- **Table 2 : i**n the corridor scene, while the average travel time of is **shorter (16.97 s)**, its average energy consumption is higher due to the inability to predict occlusion areas and a greater reliance on aerial paths.

End-to-End Performance

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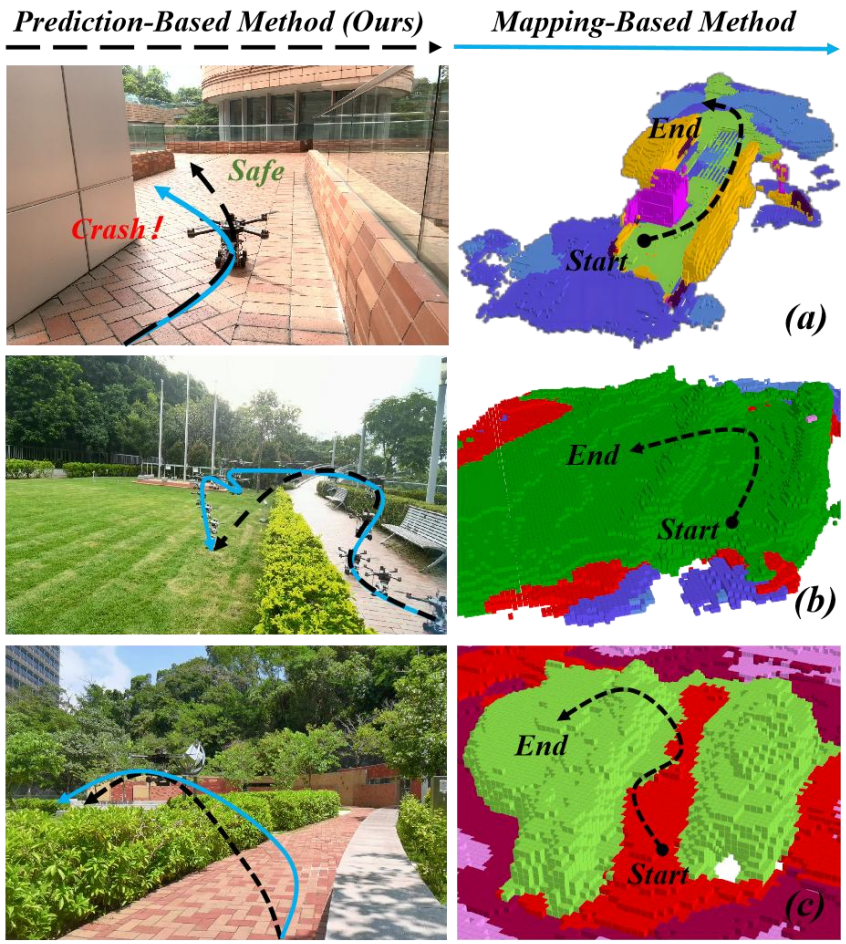
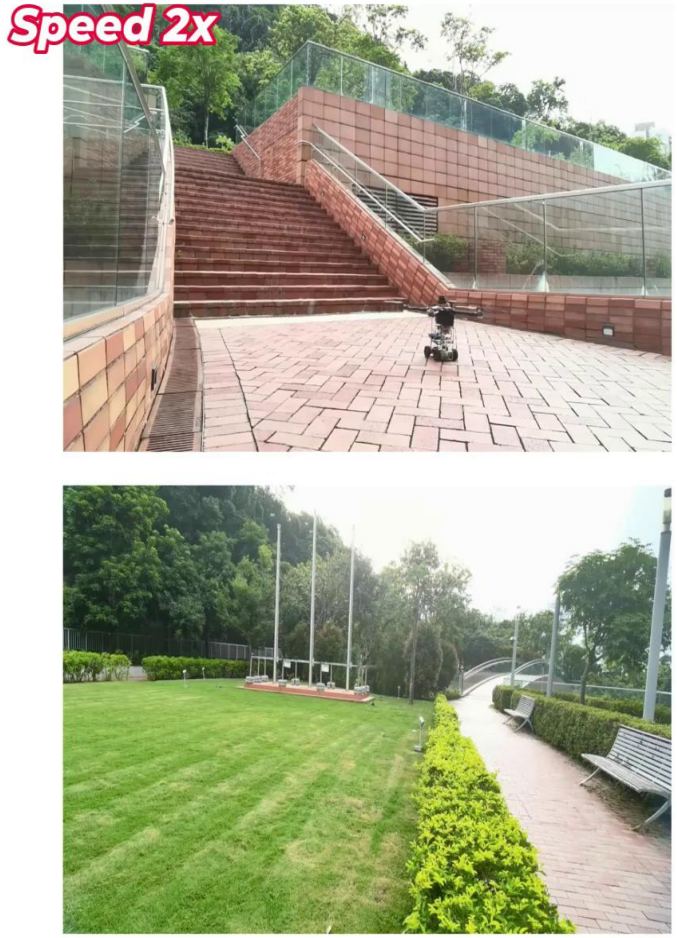
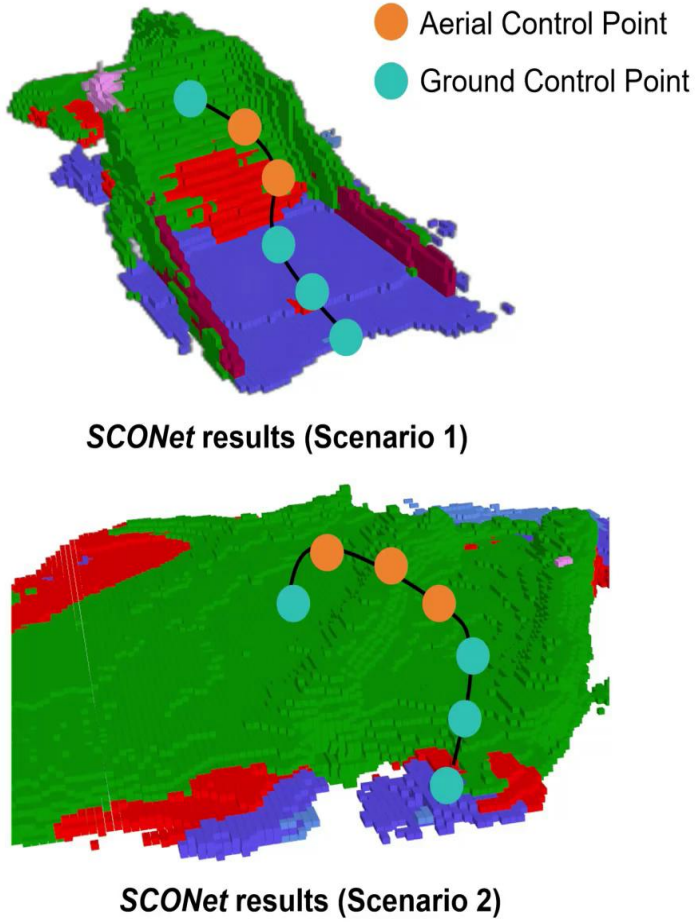
◆ Real-World Experiments:







SCONet Performance

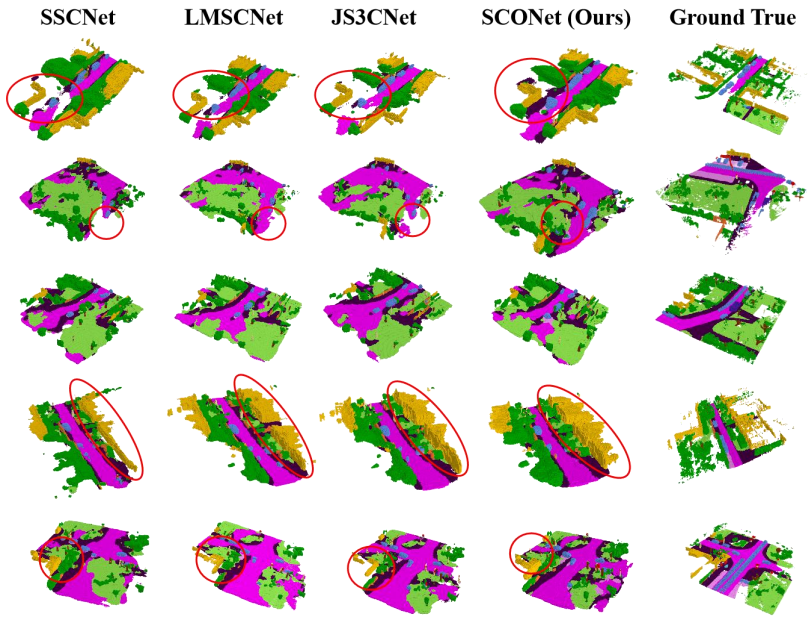


Table 3

Method	*IoU*	*Prec.*	*Recall*	*FPS*	*mIoU*
SSCNet [10]	53.20	59.13	**84.15**	12.00	14.55
SG-NN [21]	31.26	31.60	54.50	12.00	9.90
J3S3Net [22]	51.10	40.23	61.09	1.73	23.80
LMSCNet [13]	54.89	82.21	62.29	18.50	14.13
S3CNet [23]	45.60	48.79	77.13	1.82	**29.50**
TDS [24]	50.60	72.43	78.61	1.70	17.70
SCONet (our)	**56.12**	**85.02**	63.47	**20.00**	17.61

- **Table 3:** our SCONet outperforms its rivals, registering the highest IoU completion metric score of **56.12.**

- **Table 3:** despite a slightly lower mIoU compared to S3CNet and J3S3Net, SCONet's inference speed is significantly enhanced, being about **20 times faster**. This is primarily due to the adoption of depthwise separable convolutions instead of the resource-heavy 3D convolutions in its encoder, enabling real-time efficiency with **20 FPS** on an RTX 3090 GPU.

SCONet Ablation Experiment

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Method	IoU ↑	mIoU ↑
SCONet (ours)	55.50	16.10
w/o Depth-Separable Convolution	54.15	15.76
w/o Criss-Cross Attention	53.20	15.11
w/o MobileViT-v2 Attention	53.86	15.37

Ablation studies on the SemanticKITTI validation set highlight the significance of two key components in our network: ***self-attention mechanisms*** and ***depth-separable convolutions***.

- The CCA mechanism substantially impacts completion and semantic prediction by effectively aggregating context across rows and columns.
  - Without CCA causes a **4.14%** and **6.15% drop** in completion and semantic completion, respectively.
- MobileViT-v2 Attention captures local scene features, such as occluded areas, with low computational overhead.
  - Without MobileViT-v2 Attention leads to a **2.95% decline** in IoU.
- Furthermore, depth-separable convolutions significantly reduce the number of parameters.

Conclusion and Future Work

- **AGRNav, the first efficient and energy-saving autonomous navigation system for air-ground robots.**
  - SCONet, which outperforms state-of-the-art models in prediction accuracy and inference time;
  - a hierarchical path planner, improved by a query-based low-latency update method, considers obstacles in occluded areas to generate paths;
  - not only minimizes collision risk but also reduces energy consumption by 50% compared to the baseline;
  - The system's robustness has been extensively validated through experiments in both simulated and real-world environments.

- The construction of ESDF Map **takes up 70%** of the path planning time. In the future, our work will eliminate the process of building ESDF map and achieve faster and real-time path planning.

- Recent semantic scene completion work based on ***Transformer*** and ***3D convolution*** has shown high completion accuracy. In the future, we will consider combining scene completion with edge computing to deploy a computationally intensive inference prediction model at the edge.

Publications

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➢ First Author:

- **[ICRA 2024]** AGRNav: Efficient and Energy-Saving Autonomous Navigation for Air-Ground Robots in Occlusion-Prone Environments
  - ✓ ***The First AGR-Tailored Occlusion-Aware Navigation System***
- **[RA-L 2024]** HE-Nav: A High-Performance and Efficient Navigation System for Aerial-Ground Robots in Cluttered Environments
  - ✓ ***The First AGR-Tailored ESDF-Free Navigation System***
- **[RA-L 2024]** OMEGA: Efficient Occlusion-Aware Navigation for Air-Ground Robot in Dynamic Environments via State Space Model
  - ✓ ***The First AGR-Tailored Dynamic Navigation System***

➢ Other work I help with:

- **[ICCC 2024]** Prediction-based Hierarchical Reinforcement Learning for Robot Soccer
- **[ApPLIED Workshop @PODC 2024]** Hybrid-Parallel: Achieving High Performance and Energy Efficient Distributed Inference on Robots
- **[AIML Workshop @COMPSAC 2023]** New Problems in Active Sampling for Mobile Robotic Online Learning

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Thanks for listening and questions are welcome!

Name of Speaker: Junming Wang (MPhil Student)