

OMEGA: Efficient Occlusion-Aware Navigation for Air-Ground Robots in Dynamic Environments via State Space Model

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Abstract—Air-ground robots (AGR) are widely used in surveillance and disaster response due to their exceptional mobility and versatility (i.e., flying and driving). Current AGR navigation systems perform well in static occlusion-prone environments (e.g., indoors) by using 3D semantic occupancy networks to predict occlusions for complete local mapping and then computing Euclidean Signed Distance Field (ESDF) for path planning. However, these systems face challenges in dynamic scenes (e.g., crowds) due to limitations in perception networks’ low prediction accuracy and path planners’ high computation overhead. In this paper, we propose OMEGA, which contains OccMamba with an Efficient AGR-plAanner to address the above-mentioned problems. OccMamba adopts a novel architecture that separates semantic and occupancy prediction into independent branches, incorporating the mamba module to efficiently extract semantic and geometric features in 3D environments. This ensures the network can learn long-distance dependencies and improve prediction accuracy. Features are then combined within the Bird’s Eye View (BEV) space to minimise computational overhead during feature fusion. The resulting semantic occupancy map is integrated into the local map, providing occlusion awareness of the dynamic environment. Our AGR-Planner utilizes this local map and employs Kinodynamic A* search and gradient-based trajectory optimization for ESDF-free and energy-efficient planning. Experiments demonstrate that OccMamba outperforms the state-of-the-art 3D semantic occupancy network with 25.0% mIoU. End-to-end navigation experiments in dynamic scenes verify OMEGA’s efficiency, achieving a 96% average planning success rate. Code and Video Page: <https://jmwang0117.github.io/OMEGA/>.

Index Terms—Deep learning for visual perception, Autonomous navigation, 3D semantic occupancy prediction

I. INTRODUCTION

In recent years, air-ground robots (AGR) have attracted significant attention from both academia [1]–[4] and industry due to their versatile navigation capabilities in the ground and aerial domains. To enhance AGR navigation in occlusion-prone environments, existing works employ sensors, such as depth cameras, to collect point clouds. These point clouds are then processed by 3D semantic occupancy networks [5]–[8], which predict occluded areas and generate a complete local map. Based on the local map, an Euclidean Signed Distance Field (ESDF) map [2], [4] is constructed for hybrid aerial-ground path planning.

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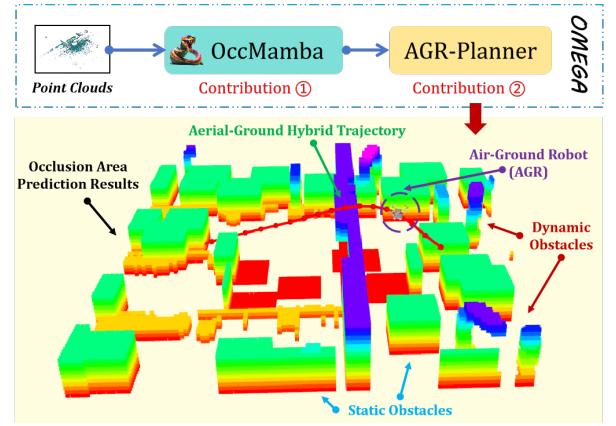


Fig. 1: OMEGA is the first AGR-specific navigation system that enables occlusion-aware mapping and pathfinding in dynamic scenarios. It integrates OccMamba for real-time obstacle prediction from point clouds and updates local maps accordingly, while AGR-Planner rapidly generates reliable paths using the updated local map.

Unfortunately, while these methods have shown success in static occlusion-prone environments (e.g., indoor or forest), they struggle in dynamic environments with moving obstacles (Fig. 1). This limitation can be attributed to two main factors: the *perception network*’s high inference latency and low prediction accuracy, and the *path planner*’s high computational overhead. Firstly, despite the improved accuracy of transformer-based 3D semantic occupancy prediction networks [9], [10] in simultaneously predicting static and dynamic obstacles for occlusion-free local mapping, their high computational overhead hinders deployment on resource-constrained AGR devices (e.g., Jetson Xavier NX). Secondly, current AGR path planners [2], [4] allocate nearly 70% of the total local planning time to construct the Euclidean Signed Distance Field (ESDF) map. This extensive processing time is impractical for dynamic environments with rapidly changing scenes, as it heightens the risk of collisions (Table I).

Our key insight to address the above limitations is to propose an efficient 3D semantic occupancy network that ensures real-time inference while improving prediction accuracy. We draw inspiration from state space models (SSMs) [11] and their improved versions, such as Mamba [12], [13]. By integrating mamba blocks into a new 3D semantic occupancy network architecture, we aim to enable the network to model long-distance dependencies and perform parallel feature learning. This approach facilitates real-time occlusion prediction

TABLE I: Comparison with baseline AGR systems.

Method	Dyn. Env.	Occl. Aware	Mov. Time	Succ. Rate	Energy
HDF [1]	x	x	x	x	x
TABV [2]	x	x	x	x	x
M-TABV [3]	x	x	x	x	x
AGRNav [4]	x	✓	x	x	✓
OMEGA (Ours)	✓	✓	✓	✓	✓

in highly dynamic environments, resulting in more complete local maps. Furthermore, while Zhou *et al.* [14] developed an ESDF-free path planner for quadcopters, it does not address AGR-specific requirements in dynamic scenarios, particularly energy efficiency and dynamic constraints. Consequently, exploring ESDF-free AGR path planners is crucial to improving overall navigation performance.

Based on these insights, We introduce OMEGA (Fig. 2), consisting of two key components: OccMamba and AGR-planner. OccMamba, the first 3D semantic occupancy network based on state-space models (SSMs), departs from previous networks that jointly learn semantics and occupancy by separating these predictions into different branches (Fig. 3). This separation enables specialized learning within each domain, improving prediction accuracy and fully leveraging the complementary properties of semantic and geometric features in the subsequent feature fusion stage. We also integrate novel Sem-Mamba and Geo-Mamba blocks into these branches to capture long-distance dependencies critical for semantic accuracy and occupancy prediction. By projecting features into the bird’s-eye view (BEV) space, we reduce fusion latency to achieve real-time inference. Prediction results are merged into the local map using a low-latency update method from [4], ensuring an up-to-date and accurate map in highly dynamic environments.

During the planning phase, we propose AGR-Planner, which builds on EGO-Swarm [14] for aerial-ground hybrid path planning. To address AGR-specific requirements, particularly energy efficiency and dynamic constraints, we add additional energy costs to motion primitives involving aerial destinations, promoting energy efficiency. Simultaneously, we account for AGRs’ non-holonomic constraints by limiting ground control point curvature. Finally, by integrating the obstacle distance estimation method from [14] and backend trajectory optimization, AGR-Planner generates ESDF-free, energy-efficient, smooth, collision-free, and dynamically feasible trajectories.

We first assessed OccMamba on the SemanticKITTI benchmark, comparing its accuracy and inference speed to some leading occupancy networks. Then, we tested OMEGA (Fig. 2) in simulated and real dynamic environments, contrasting it with two solid and open-source AGR navigation baselines, showcasing its superior efficiency. Our evaluation reveals:

- **OccMamba is efficient and real-time.** OccMamba achieves state-of-the-art performance ($mIoU = 25.0$) on the SemanticKITTI benchmark and enables high-speed inference (i.e., 22.1 FPS). (§ V-B)
- **OMEGA is efficient.** OMEGA achieved success rates of 98% in the simulation scenarios while having the shortest average movement time (i.e., 16.1s). (§ V-C)
- **OMEGA is energy-saving.** The results of real dynamic

environment navigation show that OMEGA can save about 18% of energy consumption. (§ V-D)

II. RELATED WORK

A. Dynamic Navigation System for AGRs

Numerous researchers have explored various aerial-ground robot configurations, such as incorporating passive wheels [2], [15], [16], cylindrical cages [17], or multi-limb [18] onto drones. Recently, Fan *et al.* [1] address ground-aerial motion planning. Their approach initially employs the A* algorithm to search for a geometric path as guidance, favouring ground paths by adding extra energy costs to aerial paths. Zhang *et al.* [2] proposed a path planner and controller capable of path searching, but it relies on an ESDF map. The intensive computation and limited perception of occluded areas lead to a low success rate in path planning and increased energy consumption. Wang *et al.* [4] proposed AGRNav, the first AGR navigation system with occlusion perception capability. Although it performs well in static environments, its simple perception network structure design and the defects of the path planner make it difficult to operate in complex and changing dynamic environments. Our work aims to explore new AGR navigation systems for efficient navigation in dynamic environments.

B. 3D Semantic Occupancy Prediction

3D semantic occupancy prediction is crucial for interpreting occluded environments, as it discerns the spatial layout beyond visual obstructions by merging geometry with semantic clues. This process enables autonomous systems to anticipate hidden areas, crucial for safe navigation and decision-making. Research on 3D semantic occupancy prediction can be summarized into three main streams: *Camera-based* approaches capitalize on visual data, with pioneering works like MonoScene by Cao *et al.* [5] exploiting RGB inputs to infer indoor and outdoor occupancy. Another notable work by Li *et al.* [10] is VoxFormer, a transformer-based semantic occupancy framework capable of generating complete 3D volume semantics using only 2D images. *LiDAR-based* approaches like S3CNet by Cheng *et al.* [6], JS3C-Net by Yan *et al.* [19], and SSA-SC by Yang *et al.* [20], which adeptly handle the vastness and variability of outdoor scenes via point clouds. *Fusion-based* approaches aim to amalgamate the contextual richness of camera imagery with the spatial accuracy of LiDAR data. The Openoccupancy benchmark by Wang *et al.* [21] is a testament to this synergy, providing a platform to assess the performance of integrated sensor approaches.

C. State Space Models (SSMs) and Mamba

State-Space Models (SSMs), including the S4 model [11], have proven effective in sequence modelling, particularly for capturing long-range dependencies, outperforming traditional CNNs and Transformers. The Mamba model [12], [13] builds on this by introducing data-dependent SSM layers, offering enhanced adaptability and significantly improved efficiency in processing long sequences. This has led Mamba to excel

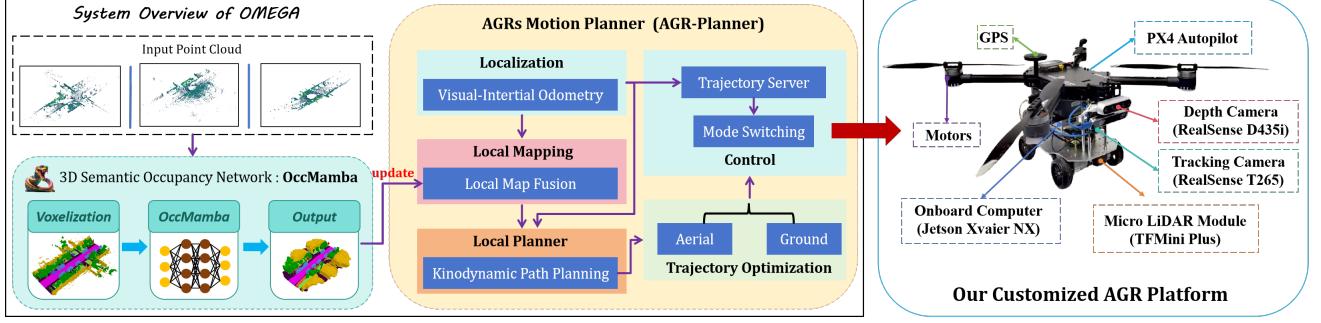


Fig. 2: OMEGA system architecture. The perception network (i.e., OccMamba) and AGR-planner run asynchronously on the onboard computer, connected through a query-based map update method from [4] to ensure real-time local map updates with prediction results.

in various domains, including robot manipulation [22], point cloud analysis [23], [24], and video understanding [25], due to its scalability and versatility. Leveraging Mamba's strengths, we developed OccMamba, the first mamba-based 3D semantic occupancy prediction network to learn long-distance dependencies for understanding dynamic scenes.

III. 3D SEMANTIC OCCUPANCY NETWORK OF OMEGA

OccMamba (Fig. 3) features three branches: semantic, geometric, and BEV fusion. The semantic and geometric branches are supervised by multi-level auxiliary losses, which are removed during inference. Multi-scale features generated by these two branches are fused in the BEV space to alleviate the computational overhead caused by dense feature fusion.

A. OccMamba Network Structure

Semantic Branch: The semantic branch consists of a voxelization layer and three encoder Sem-Mamba Blocks with the same structures. The input point cloud $P \in \mathbb{R}^{N \times 3}$ is converted to a multi-scale voxel representation at a voxel resolution s by the voxelization layer. These voxels are then aggregated by maximum pooling to obtain a unified feature vector for each voxel. The vectors from different scales are merged to form the final voxel feature V_{f_m} , with a size of $L \times W \times H$, where f_m represents the voxel index. The semantic features $\{S_f^1, S_f^2, S_f^3\}$ are projected into the bird's-eye view (BEV) space by assigning a unique BEV index to each voxel based on its f_m value. Features sharing the same BEV index are aggregated using max pooling, resulting in sparse BEV features. These sparse features are then densified using the densification function of Spconv [26] to produce dense BEV features $\{BEV_f^{sem,1}, BEV_f^{sem,2}, BEV_f^{sem,3}\}$.

Sem-Mamba Block: Mamba [12], [13], a selective state-space model, has recently outperformed CNN- and Transformer-based approaches in various vision tasks due to its efficient long-distance sequence modelling and linear-time complexity. These characteristics make Mamba promising for improving 3D semantic occupancy prediction accuracy while maintaining fast reasoning in dynamic environments. Inspired by mamba's success, we introduce the Sem-Mamba block as the semantic branch encoder in our network to enable efficient semantic representation learning. Specifically, state space models [11] introduce hidden states $h(t) \in \mathbb{R}^N$ to map inputs $x(t) \in \mathbb{R}^L$

to outputs $y(t)$, with the continuous state space dynamics governed by:

$$\dot{h}'(t) = \mathbf{A}h(t) + \mathbf{B}x(t), y(t) = \mathbf{C}h(t) \quad (1)$$

Using a time scale parameter Δ , the Mamba model discretizes the continuous parameters, yielding the discretized state space equations:

$$\bar{\mathbf{A}} = \exp(\Delta \mathbf{A}), \bar{\mathbf{B}} = (\Delta \mathbf{A})^{-1}(\exp \Delta (\mathbf{A}) - \mathbf{I}) \cdot \Delta \mathbf{B} \quad (2)$$

$$h(t) = \bar{\mathbf{A}}h_{t-1} + \bar{\mathbf{B}}x_t, y_t = \mathbf{C}h_t \quad (3)$$

The global convolution kernel $\bar{\mathbf{K}} \in \mathbb{R}^L$ is used to calculate the output y :

$$\bar{\mathbf{K}} = (C\bar{B}, C\bar{AB}, \dots, C\bar{A}^{m-1}\bar{B}), y = x * \bar{\mathbf{K}} \quad (4)$$

In each Sem-Mamba Block, dense BEV features serve as the input x to the mamba module (Fig. 3). By applying discretized SSM dynamics and global convolution kernels, the mamba block effectively processes the BEV features, resulting in an enhanced feature representation with richer long-distance dependencies. This enhanced representation improves the performance of semantic occupancy prediction by capturing and strengthening the spatial relationships between semantic elements. Meanwhile, mamba block's parallel feature learning properties ensure real-time reasoning in dynamic environments.

Geometry Branch and Geo-Mamba Block: The geometric branch (Fig. 3) begins with an input layer using a $7 \times 7 \times 7$ kernel and comprises three Geo-Mamba blocks as the encoder. Each Geo-Mamba block maintains a consistent architecture, combining a residual block with a mamba module and a BEV projection module. The residual block first processes the voxels $V \in \mathbb{R}^{1 \times L \times W \times H}$ obtained from the point cloud, and its output features serve as the input x to the mamba module. The mamba module generates multi-scale dense geometric features $\{G_f^1, G_f^2, G_f^3\}$, which enrich the captured geometric details. By leveraging the mamba module's ability to capture long-distance dependencies with linear complexity, the geometric branch can effectively process and refine the geometric information within the voxels. Subsequently, the dense 3D features are aligned along the z axis, and 2D convolutions are applied to compress the feature dimensions. This step produces dense

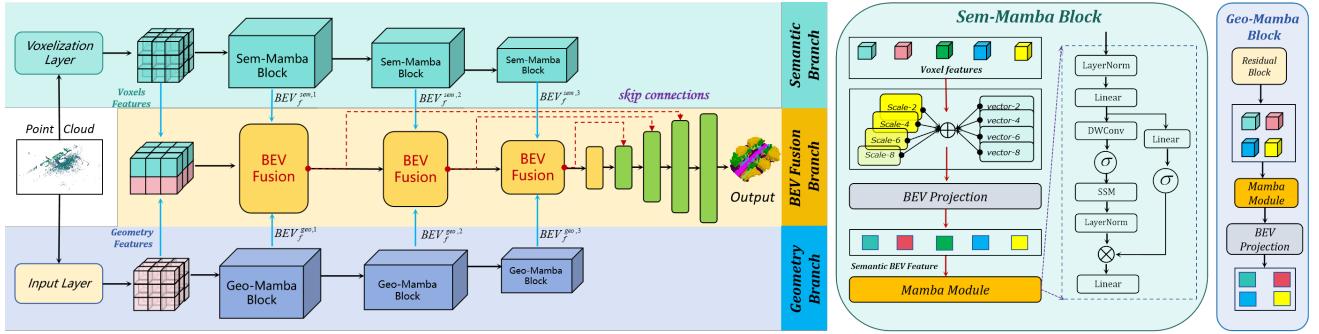


Fig. 3: The overview of the proposed OccMamba. It consists of semantic, geometry and BEV fusion branches. Meanwhile, lightweight MLPs serve as auxiliary heads during training, attached after each encoder block in the semantic and completion branches for voxel predictions. At the inference stage, these heads are detached to preserve a streamlined network architecture.

BEV features $\{BEV_f^{com,1}, BEV_f^{geo,2}, BEV_f^{geo,3}\}$, which are suitable for fusion with the semantic features (Fig. 3).

BEV Feature Fusion Branch: Our BEV fusion branch adopts a U-Net architecture with 2D convolutions. The encoder consists of an input layer and four residual blocks, where the resolution of the first three residual blocks corresponds to the resolution of the semantic and geometric branches. After each residual block, a feature fusion module from [27] is employed to take the output of the previous stage and the semantic/geometric representation at the same scale as the input. This module outputs fused features that contain informative semantic context and geometric structure. The decoder upscales the compressed features from the encoder three times, through skip connections. These skip connections allow the decoder to recover spatial details that may have been lost during the encoding process, thereby improving the overall quality of the output. Finally, the last convolution layer of the decoder generates the 3D semantic occupancy prediction: $\mathcal{O} \in \mathbb{R}^{((C_n+1)*L)*H*W}$, where C_n is the number of semantic classes.

B. Optimization

Based above of our methods above, there are four main terms in our loss function. The semantic loss L_{sem} is the sum of the lovasz loss [28] and cross-entropy loss [29] at each stage of the semantic branch:

$$L_{sem} = \sum_{i=1}^3 (L_{cross,i} + L_{lovasz,i}) \quad (5)$$

The training loss L_{com} for this branch is calculated as follows:

$$L_{com} = \sum_{i=1}^3 (L_{binary_cross,i} + L_{lovasz,i}) \quad (6)$$

where i denotes the i -th stage of the completion branch and L_{binary_cross} indicates the binary cross-entropy loss. The BEV loss L_{bev} is :

$$L_{bev} = 3 \times (L_{cross} + L_{lovasz}) \quad (7)$$

We train the whole network end-to-end. The overall objective function is:

$$L_{total} = L_{bev} + L_{sem} + L_{com} \quad (8)$$

where L_{bev} , L_{sem} and L_{com} respectively represent BEV loss, the semantic loss and completion loss.

IV. AGR MOTION PLANNER

We introduce AGR-Planner, a novel gradient-based local planner tailored for AGRs built upon EGO-Swarm [14]. It features a Kinodynamic A* algorithm for efficient pathfinding and a gradient-based method for trajectory optimization, streamlining the planning process.

A. Kinodynamic Hybrid A* Path Searching

Our AGR-Planner begins by generating a preliminary "initial trajectory" ι (see Fig. 4a), which initially disregards obstacles by incorporating random coordinate points, anchored by the start and end locations. Subsequently, for any "collision trajectory segment" found within obstacles, we employ the kinodynamic A* algorithm to create a "guidance trajectory segment" τ . This segment is defined using motion primitives rather than straight lines for edges during the search, incorporating additional energy consumption metrics for flying (Fig. 4a). This approach encourages the planning of ground trajectories, resorting to aerial navigation only when confronting significant obstacles, thus optimizing energy efficiency.

B. Gradient-Based B-spline Trajectory Optimization

B-spline Trajectory Formulation: In trajectory optimization (Fig. 4b), the trajectory is parameterized by a uniform B-spline curve Θ , which is uniquely determined by its degree p_b , N_c control points $\{Q_1, Q_2, Q_3, \dots, Q_{N_c}\}$, and a knot vector $\{t_1, t_2, t_3, \dots, t_{M-1}, t_M\}$, where $Q_i \in \mathbb{R}^3$, $t_m \in \mathbb{R}$, $M = N + p_b$. Following the matrix representation of the [4] the value of a B-spline can be evaluated as:

$$\Theta(u) = [1, u, \dots, u^p] \cdot M_{p_b+1} \cdot [Q_{i-p_b}, Q_{i-p_b+1}, \dots, Q_i]^T \quad (9)$$

where M_{p_b+1} is a constant matrix depends only on p_b . And $u = (t - t_i)/(t_{i+1} - t_i)$, for $t \in [t_i, t_{i+1}]$. In particular, in ground mode, we assume that AGR is driving on flat ground so that the vertical motion can be omitted and we only need to consider the control points in the two-dimensional horizontal plane, denoted as $Q_{ground} = \{Q_{t0}, Q_{t1}, \dots, Q_{tM}\}$,

where $Q_{ti} = (x_{ti}, y_{ti}), i \in [0, M]$. In aerial mode, the control points are denoted as Q_{aerial} . According to the properties of B-spline: the k^{th} derivative of a B-spline is still a B-spline with order $p_{b,k} = p_b - k$, since Δt is identical along Θ , the control points of the velocity V_i , acceleration A_i and jerk J_i curves are obtained by:

$$V_i = \frac{Q_{i+1} - Q_i}{\Delta t}, A_i = \frac{V_{i+1} - V_i}{\Delta t}, J_i = \frac{A_{i+1} - A_i}{\Delta t} \quad (10)$$

Collision Avoidance Force Estimation: For each control point on the collision trajectory segment, vector v (i.e., a safe direction pointing from inside to outside of that obstacle) is generated from ν to τ and p is defined at the obstacle surface (in Fig. 4a). With generated $\{p, v\}$ pairs, the planner maximizes D_{ij} and returns an optimized trajectory. The obstacle distance D_{ij} if i^{th} control point Q_i to j^{th} obstacle is defined as:

$$D_{ij} = (Q_i - p_{ij}) \times v_{ij} \quad (11)$$

Because the guide path τ is energy-saving, the generated path is also energy efficient (in Fig. 4a). Inspired by [14], we discover multiple viable paths that navigate through different local minima in a dynamic environment. This is achieved by generating distance fields in various directions through reversing vector v_1 to obtain $v_2 = -v_1$. Following this, a search process identifies a new anchor point p_2 on the obstacle's surface along v_2 , as shown in Fig. 4a. This approach enables us to evaluate alternative trajectories and select the most cost-effective path for navigation.

Air-Ground Hybrid Trajectory Optimization: Based on the special properties of AGR bimodal, we first adopt the following cost terms designed by Zhou *et al.* [14]:

$$\min_Q J_{AGR} = \sum \lambda_\phi J_\phi \quad (12)$$

where $\phi = \{s, c, d, t\}$ and the subscripted λ indicates the corresponding weights. In addition, J_s is the smoothness penalty, J_c is for collision, J_d is for dynamically feasibility, and J_t is for terminal progress. $\lambda_s, \lambda_c, \lambda_d, \lambda_t$ are weights for each cost terms. Meanwhile, J_s and J_t belongs to *minimum error* which minimize the total error between a linear transformation of decision variables $L(Q)$ and a desired value D . J_c and J_d belongs to *soft barrier constraint* which penalize decision variables exceeding a specific threshold ζ . Subsequently, based on our observations, AGR also faces non-holonomic constraints when driving on the ground, which means that the ground velocity vector of AGR must be aligned with its yaw angle. Additionally, AGR needs to deal with curvature limitations that arise due to minimizing tracking errors during sharp turns. Therefore, a cost for curvature needs to be added, and J_n can be formulated as:

$$J_n = \sum_{i=1}^{M-1} F_n(Q_{ti}) \quad (13)$$

where $F_n(Q_{ti})$ is a differentiable cost function with C_{max} specifying the curvature threshold:

$$F_n(Q_{ti}) = \begin{cases} (C_i - C_{max})^2, & C_i > C_{max}, \\ 0, & C_i \leq C_{max} \end{cases} \quad (14)$$

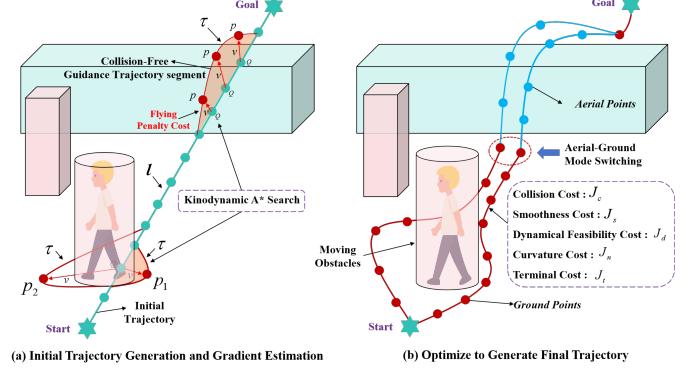


Fig. 4: AGR-Planner and topological trajectory generation.

where $C_i = \frac{\Delta \beta_i}{\Delta Q_{ti}}$ is the curvature at Q_{ti} , and the $\Delta \beta_i = \left| \tan^{-1} \frac{\Delta y_{ti+1}}{\Delta x_{ti+1}} - \tan^{-1} \frac{\Delta y_{ti}}{\Delta x_{ti}} \right|$. In general, the overall objective function is formulated as follows:

$$\min_Q J_{AGR} = \lambda_s J_s + \lambda_c J_c + \lambda_d J_d + \lambda_t J_t + \lambda_n J_n \quad (15)$$

The optimization problem is addressed with the NLopt. Meanwhile, the same methods as in [4] are used for trajectory tracking and control, as well as additional mode switching.

V. EVALUATION

We evaluate OccMamba on the SemanticKITTI benchmark and integrate the best pre-trained model with AGR-Planner to establish our comprehensive **OMEGA** system. We then assess OMEGA's autonomous navigation efficiency for AGRs in simulated and real-world dynamic environments, focusing on metrics like planning success rate, average movement and planning time, and energy consumption. Finally, ablation experiments verify the navigation efficiency improvements brought by OMEGA's two key components.

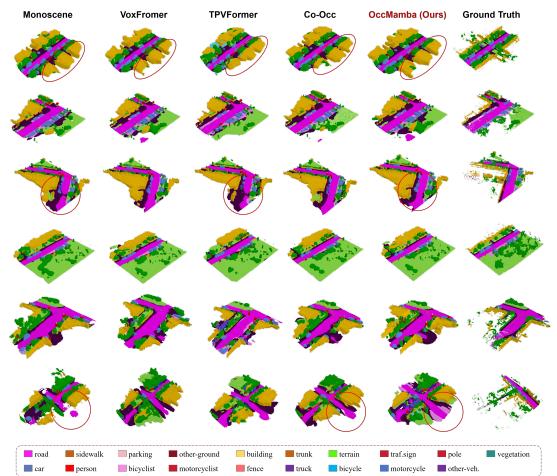


Fig. 5: Results of a qualitative comparison on the SemanticKITTI validation set are presented, showcasing various models.

A. Evaluation setup

3D Semantic Occupancy Network: We trained OccMamba on the outdoor SemanticKITTI dataset [33] using a single

TABLE II: 3D Semantic occupancy prediction results on SemanticKITTI test set. The C and L denote Camera and LiDAR.

Method	Modality	IoU ↑	mIoU ↑																		FPS		
				road (15.30%)	sidewalk (11.13%)	parking (0.12%)	other-ground (0.56%)	building (14.1%)	car (3.92%)	truck (0.16%)	bicycle (0.03%)	motorcycle (0.03%)	other-veh. (0.20%)	vegetation (9.36%)	trunk (0.51%)	terrain (0.17%)	person (0.07%)	bicyclist (0.07%)	motorcyclist. (0.05%)	fence (3.90%)	pole (0.29%)	traf.-sign (0.08%)	
MonoScene [5]	C	34.2	11.1	54.7	27.1	24.8	5.7	14.4	18.8	3.3	0.5	0.7	4.4	14.9	2.4	19.5	1.0	1.4	0.4	11.1	3.3	2.1	1.1
OccFormer [9]	C	34.5	12.3	55.9	30.3	31.5	6.5	15.7	21.6	1.2	1.5	1.7	3.2	16.8	3.9	21.3	2.2	1.1	0.2	11.9	3.8	3.7	1.8
VoxFormer [10]	C	43.2	13.4	54.1	26.9	25.1	7.3	23.5	21.7	3.6	1.9	1.6	4.1	24.4	8.1	24.2	1.6	1.1	0.0	6.6	5.7	8.1	1.5
TPVFormer [30]	C	34.3	11.3	55.1	27.2	27.4	6.5	14.8	19.2	3.7	1.0	0.5	2.3	13.9	2.6	20.4	1.1	2.4	0.3	11.0	2.9	1.5	1.0
LMSNet [31]	L	55.3	17.0	64.0	33.1	24.9	3.2	38.7	29.5	2.5	0.0	0.0	0.1	40.5	19.0	30.8	0.0	0.0	0.0	20.5	15.7	0.5	21.3
SSC-RS [27]	L	59.7	24.2	73.1	44.4	38.6	17.4	44.6	36.4	5.3	10.1	5.1	11.2	44.1	26.0	41.9	4.7	2.4	0.9	30.8	15.0	7.2	16.7
SCONet [4]	L	56.1	17.6	51.9	30.7	23.1	0.9	39.9	29.1	1.7	0.8	0.5	4.8	41.4	27.5	28.6	0.8	0.5	0.1	18.9	21.4	8.0	20.0
M-CONet [21]	C&L	55.7	20.4	60.6	36.1	29.0	13.0	38.4	33.8	4.7	3.0	2.2	5.9	41.5	20.5	35.1	0.8	2.3	0.6	26.0	18.7	15.7	1.4
Co-Occ [32]	C&L	56.6	24.4	72.0	43.5	42.5	10.2	35.1	40.0	6.4	4.4	3.3	8.8	41.2	30.8	40.8	1.6	3.3	0.4	32.7	26.6	20.7	1.1
OccMamba (Ours)	L	59.9	25.0	72.9	44.8	42.7	18.1	44.2	36.1	3.5	12.3	6.0	10.1	44.6	29.5	42.1	5.9	2.9	0.4	32.2	17.6	8.1	22.1

TABLE III: 3D occupancy results on SemanticKITTI [33] validation set.

Method	IoU (%)	mIoU (%)	Prec. (%)	Recall (%)	Params(M)	FLOPs(G)	Mem. (GB)
<i>MLP/CNN-based</i>							
Monoscene [5]	37.1	11.5	52.2	55.5	149.6	501.8	20.3
NDC-Scene [34]	37.2	12.7	-	-	-	-	20.1
Symphonies [8]	41.9	14.9	62.7	55.7	59.3	611.9	20.0
<i>Transformer-based</i>							
OccFormer [9]	36.5	13.5	47.3	60.4	81.4	889.0	21.0
VoxFormer [10]	57.7	18.4	69.9	76.7	57.8	-	15.2
TPVFormer [30]	35.6	11.4	-	-	48.8	946.0	20.0
CGFormer [35]	45.9	16.9	62.8	63.2	122.4	314.5	19.3
<i>Mamba-based (Ours)</i>							
OccMamba	58.6	25.2	77.8	70.5	23.8	505.1	3.5

NVIDIA 3090 GPU. The dataset provides LiDAR point clouds for semantic occupancy prediction, with ground truth represented as [256, 256, 32] voxel grids (each voxel measuring $0.2m^3$). Training spanned 80 epochs with a batch size of 6, utilizing the AdamW optimizer [36] with an initial learning rate of 0.001. We applied random x-y axis flipping for input point cloud augmentation. The total training time was approximately 40 hours.

Simulation Experiment: We conducted our simulation experiments on a laptop running Ubuntu 20.04 with an NVIDIA RTX 4060 GPU. The experiments took place in a $20m \times 20m \times 5m$ simulated environment, and a total of 200 trials were performed. The first set of 100 trials featured an environment populated with 80 walls and 20 rings, while the second set of 100 trials included 80 moving cylinders and 20 stationary rings. To generate a diverse range of occlusions and unknown areas, the positions of the obstacles were varied in each trial (Fig. 6). The objective was for the AGR equipped with OMEGA to navigate through these environments while avoiding collisions.

Real-world Experiment: In our real-world experiments, OMEGA was deployed on a custom AGR platform (Fig. 2) equipped with a RealSense D435i for point cloud acquisition, a T265 camera for visual-inertial odometry, and a for real-time onboard computation. The best-performing pre-trained OccMamba model (IoU=59.9) was deployed offline, using the same settings from AGRNav [4]. Optimized with TensorRT on Jetson Xavier NX, it efficiently completed local maps for smooth navigation. Our evaluation focused on the following key questions:

RQ1: How does OccMamba’s efficiency compare to baseline models? (§ V-B)

RQ2: How well does OMEGA navigate in dynamic simulation environments? (§ V-C)

RQ3: How effectively does OMEGA navigate in five real-world dynamic scenarios? (§ V-D)

B. OccMamba Comparison against the state-of-the-art.

Quantitative Results: OccMamba has achieved state-of-the-art performance on the SemanticKITTI hidden test dataset, boasting a completion IoU of 59.9% and a mIoU of 25.0% (Table II). While recent methods (e.g., M-CONet [21] and Co-OCC [32]) have shown commendable performance in semantic occupancy prediction tasks, OccMamba outperforms the latter by a notable margin of 5.8% in IoU. This leap in accuracy is achieved solely by utilising point cloud data, without the need for other modalities inputs, simplifying integration and deployment in real-world robotic applications. In addition, OccMamba’s efficiency parallels its performance; it integrates a linear-time mamba block within a compact, multi-branch network architecture and employs BEV feature fusion, culminating in a lean framework, weighing only 23.8MB (Table III). Meanwhile, OccMamba operates on a modest 3.5GB of GPU memory per training batch and impresses with an inference speed of 22.1 FPS, markedly outpacing existing methods like Monoscene [5] and TPVFormer [30] by a factor of 20.

Qualitative Results: In the visualizations on the SemanticKITTI validation set (Fig. 3), OccMamba demonstrates excellent semantic occupancy predictions in occlusion areas, particularly for complex or moving categories such as “vegetation”, “terrain”, “person”, and “bicycle”, aligning with the quantitative results in Table II. These reliable predictions are essential for subsequent path planning.

TABLE IV: Ablation Study on SemanticKITTI Validation Set.

Method	IoU ↑	mIoU ↑	Prec.	Recall	F1
OccMamba	58.6	25.2	77.8	70.5	73.9
w/o Geo-Mamba Block	58.2	24.7	76.4	69.8	72.8
w/o Sem-Mamba Block	57.8	24.1	76.1	69.5	72.5

Ablation Study: The ablation experiments on the SemanticKITTI validation set (Table IV) underscore the significance of the Sem-Mamba and Geo-Mamba blocks in our network architecture. Separating semantic and geometric feature processing promotes focused representation learning and leverages their synergistic effects. Removing the Sem-Mamba block results in a substantial 4.37% drop in mIoU, highlighting its vital role in accurate semantic segmentation and nuanced scene element classification.

C. Simulated Air-Ground Robot Navigation

We conducted a comparative analysis of our OMEGA system, TABV [2] and AGRNav [1]. Through 200 trials with varied obstacle placements, we evaluated the average moving time, planning time, and success rate (i.e., collision-free) of each system (Fig. 6c). In dynamic environments, our system OMEGA demonstrates an average planning success rate of 98% (Fig. 6c). This achievement stems not solely from OccMamba’s real-time and precise mapping of occluded areas, which facilitates complete local map acquisition for planning, but also from the innovative design of our AGR-Planner, which plans multiple candidate trajectories without the need for an ESDF map. When benchmarked against two ESDF-reliant navigation baselines, our AGR-Planner reduces planning time by a substantial 89.33% (Fig. 6c). This synergy between OccMamba’s detailed environmental perception and AGR-Planner’s efficient path computation guarantees swift and reliable navigation for AGRs in complex, dynamically changing, and visually obstructed scenarios.

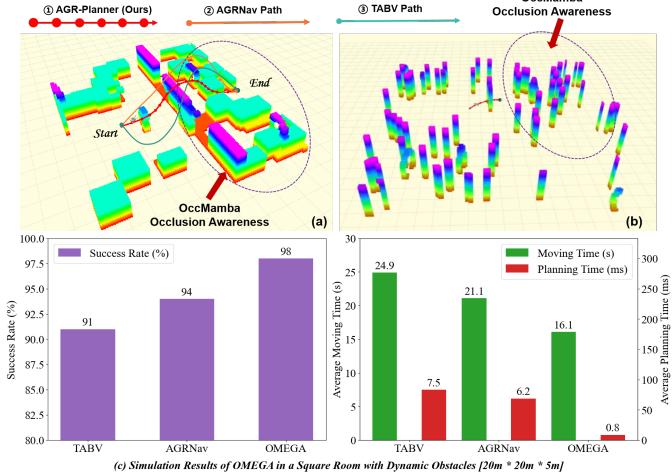


Fig. 6: Comparative Analysis of OMEGA with Baseline Systems AGRNav [4] and TABV [2]: Quantitative and Qualitative Insights in Simulation Environments.

Ablation Study: Ablation experiments (Table V) demonstrate that OccMamba contributes more to OMEGA’s planning success than SCONet, improving it by 4% and 1%, respectively. Moreover, replacing the SCONet in [4] with OccMamba enhances AGRNav’s success rate by 2%. This experiment highlights the synergy between OccMamba and AGR-Planner in achieving efficient navigation.

TABLE V: Ablation Study of OMEGA

Percep.	Plan.	Succ. Rate (%)	Plan. Time (s)
OccMamba	H-Planner [4]	96	6.5
SCONet [4]	AGR-Planner	95	0.8
-	AGR-Planner	94	0.7
OccMamba	AGR-Planner	98	0.8

D. Real-world Air-Ground Robot Navigation

We demonstrated OMEGA’s superior efficiency and energy conservation in 5 dynamic scenarios with a velocity cap of 1.5 m/s. Each navigation method was tested 10 times per scenario for reliable performance comparison. We achieved a notable 96% average success rate (Fig. 7a) in 5 dynamic scenarios with OMEGA, exhibiting lower average energy consumption relative to competitors (Fig. 7c). Specifically, in scenarios B and C, OMEGA recorded energy reductions of 22.1% and 17.28%, respectively, against AGRNav. These improvements are largely due to our OccMamba module’s swift computational ability to predict obstacle distributions in non-visible areas, enabling the AGR system to avoid potential impediments. When integrated with the AGR-Planner, this foresight allows for the rapid generation of multiple candidate paths, optimizing for both energy efficiency and reduced traversal time (Fig. 7b). Please zoom in on Fig. 7 to see more detailed qualitative and quantitative results.

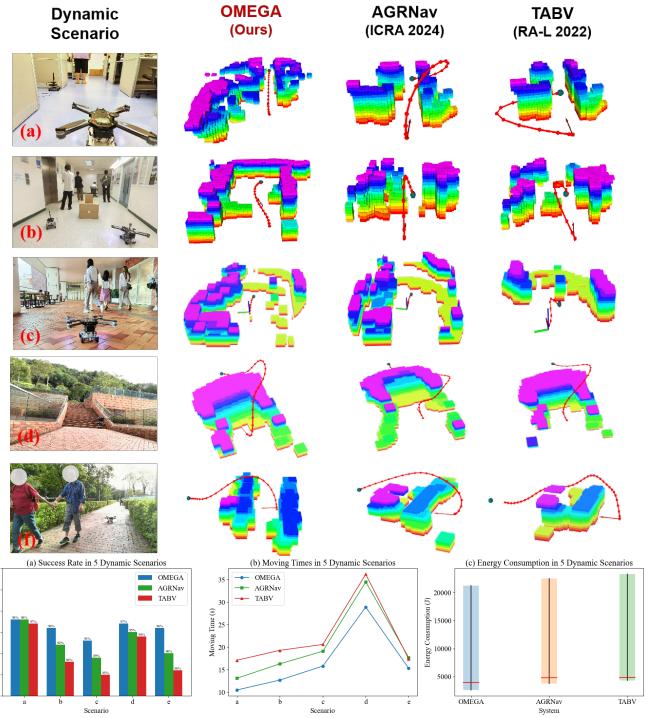


Fig. 7: Comparative Analysis of OMEGA with Baseline Systems AGRNav [4] and TABV [2]: Quantitative and Qualitative Insights in 5 real-world dynamic environments.

VI. CONCLUSION

In this letter, we introduce OMEGA, an advanced system for air-ground robot (AGR) navigation in dynamic environments. The system includes OccMamba, which efficiently

separates semantic prediction and scene completion, using mamba blocks for fast and precise real-time semantic occupancy mapping. This creates a comprehensive local map without occlusions. Based on the local map, the AGR-Planner component of OMEGA generates safe, smooth, and dynamically feasible trajectories. Our extensive testing shows that OccMamba outperforms state-of-the-art methods with a 59.9% IoU at 22.1 FPS. When integrated into the OMEGA system, the combination of OccMamba and AGR-Planner results in an impressive 96% average success rate for planning in real-world dynamic scenarios.

VII. ACKNOWLEDGMENTS

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