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Learning to Explore A Curiosity Aware Zero-Shot Framework for UAV Navigation in Indoor Environments

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Abstract. Unmanned Aerial Vehicles (UAVs) require robust exploration strategies to operate effectively in unknown indoor environments. Traditional methods often rely on prior training data or environment-specific models, limiting their adaptability in novel scenarios. In this paper, we propose a Curiosity-Aware Zero-Shot Framework that integrates an Intrinsic Curiosity Module (ICM) with a domain-randomized Zero-Shot planner to enable efficient and autonomous UAV exploration without retraining. Our framework is trained in simulated environments with randomized layouts to promote generalization and evaluated in unseen 3D indoor scenes. Experimental results show that our method significantly outperforms baselines such as Random Walk, Greedy Frontier, ICM-only, and Zero-Shot-only planners, achieving 89.7% coverage, 1.6 path efficiency, 328 seconds exploration time, and a 94.5% success rate. The ablation study highlights the complementary role of both ICM and Zero- Shot components. This work presents a scalable solution for real-time UAV navigation and contributes to the development of intelligent aerial systems capable of learning to explore novel environments autonomously.

Keywords: deep reinforcement learning; aeronavigation; zero-shot learning; intrinsic curiosity module; autonomous exploration

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become critical assets in various applications such as search and rescue, environmental monitoring, and infrastructure inspection due to their mobility and aerial perspective. One of the fundamental challenges in autonomous UAV deployment is efficient exploration of unknown environments. Traditional UAV exploration approaches rely heavily on prior training data or environment-specific models, which limits their adaptability in novel or unseen scenarios.

Inspired by the way humans and animals explore unfamiliar spaces using intrinsic motivation and learned experiences, recent research has focused on integrating curiosity-driven learning and Zero-Shot generalization into robotic systems. Curiosity modules, such as the Intrinsic Curiosity Module (ICM), enable agents to self-motivate exploration even in the absence of external rewards, while Zero-Shot learning aims to allow agents to generalize their skills to new environments without additional retraining. Combining these two paradigms offers a promising direction to build truly autonomous, efficient, and generalizable UAV exploration systems.

Despite advances in deep reinforcement learning and visual navigation, most existing UAV exploration systems struggle to adapt to unseen environments without fine-tuning or retraining. Furthermore, current Zero-Shot navigation approaches often neglect the benefits of curiosity-based intrinsic motivation, resulting in inefficient or non-purposeful exploration in unfamiliar domains.

This research aims to design a curiosity-aware Zero-Shot navigation framework that enables UAVs to efficiently explore unfamiliar environments without requiring retraining. Our goal is to mimic a learning-to-explore paradigm where the UAV is equipped with intrinsic motivation and generalizable planning capabilities to autonomously navigate novel scenarios.

To achieve this, we propose a two-stage approach. First, a curiosity-driven exploration policy is trained using the Intrinsic Curiosity Module (ICM) to learn meaningful navigation behavior in a source environment. Second, a Zero-Shot planner is deployed that transfers the exploration knowledge to new target environments using domain randomization techniques. This approach allows UAVs to adapt to diverse scenes and structures without requiring access to task-specific data in the new

environment.

The proposed system is trained in a simulated environment with varying layouts and object placements to build robust exploration capabilities. During inference, the UAV uses the pretrained curiosity module and planner to explore target environments, collecting and comparing trajectories in terms of coverage efficiency, path smoothness, and exploration time. The system is evaluated on multiple unseen 3D environments to demonstrate generalization and performance.

The main contributions of this paper are as follows. We introduce a novel Curiosity-Aware Zero-Shot framework for UAV navigation in unseen environments, enabling autonomous and efficient exploration without retraining. This framework integrates an Intrinsic Curiosity Module (ICM) with a domain- randomized planner to promote intrinsic motivation and robust generalization across diverse environments. Furthermore, we present a comprehensive evaluation demonstrating its superior performance in exploration coverage, path efficiency, and adaptability when compared to baseline methods in multiple novel environments. In summary, this work introduces a practical and scalable solution for real-time autonomous UAV exploration in unseen environments, combining intrinsic curiosity with zero-shot generalization, and lays the foundation for future research in building intelligent aerial systems capable of learning to explore efficiently in the wild.

Autonomous exploration using Unmanned Aerial Vehicles (UAVs) has emerged as a critical area of study within robotics, particularly for applications such as disaster response, environmental mapping, and infrastructure inspection in GPS- denied or previously unseen environments. These tasks require UAVs to operate with minimal human intervention while efficiently covering unknown areas, often in challenging or un- structured settings. Traditional exploration strategies typically depend on Simultaneous Localization and Mapping (SLAM) algorithms, frontier-based planning, or rule-based heuristics to guide the agent's behavior. Although these methods have demonstrated success in controlled or structured environments, their performance tends to degrade when deployed in highly dynamic, cluttered, or irregular spaces due to rigid assumptions, sensitivity to sensor noise, and reliance on handcrafted logic. Complementing these, curiosity-driven reinforcement learning (RL) leverages intrinsic motivation internal signals that encourage agents to seek novel or uncertain states. This addresses the challenge of sparse or unavailable external re- wards, enabling agents to learn exploration behaviors without external supervision. Despite their effectiveness in learning exploration, intrinsic motivation approaches often suffer from limited generalization across different environments, making them less suitable for direct deployment in novel settings.

Zero-Shot Learning (ZSL) aims to enable intelligent agents to generalize learned knowledge and behaviors to novel environments without requiring further retraining. This paradigm is especially valuable in UAV navigation tasks, where deploying a model in new, unseen scenarios is often costly or impractical due to the need for data collection, fine-tuning, or task-specific adaptation. In the context of autonomous exploration, Zero- Shot Transfer allows a UAV trained in a set of source domains, typically simulated environments to directly operate in new target domains, such as real-world environments with different layouts, textures, lighting conditions, or sensor noise. To achieve this, many recent approaches employ techniques such as domain randomization, which exposes the agent to a wide variety of variations during training to encourage robustness; or meta-learning, which focuses on training agents that can quickly adapt to new tasks with minimal data. These methods attempt to close the sim-to-real gap by promoting the learning of abstract skills that are transferable across environments, crucial for robustness against unexpected dynamics or sensory observations.

Curiosity-driven learning has emerged as a compelling approach for enabling self-supervised exploration in autonomous agents. Unlike traditional reinforcement learning that depends on external rewards, curiosity-based methods rely on intrinsic motivation to drive behavior through mechanisms like the Intrinsic Curiosity Module (ICM) or Random Network Distillation (RND), which generate internal reward signals based on novelty or prediction error. When integrated with Zero- Shot Transfer learning, curiosity-driven exploration offers a powerful synergistic effect. While Zero-Shot techniques pro- vide the capacity for generalization across domains, curiosity modules act as adaptive engines that guide exploration in novel environments, even when the agent has no prior task-specific knowledge. The agent is actively drawn toward informative and previously unvisited areas, improving state

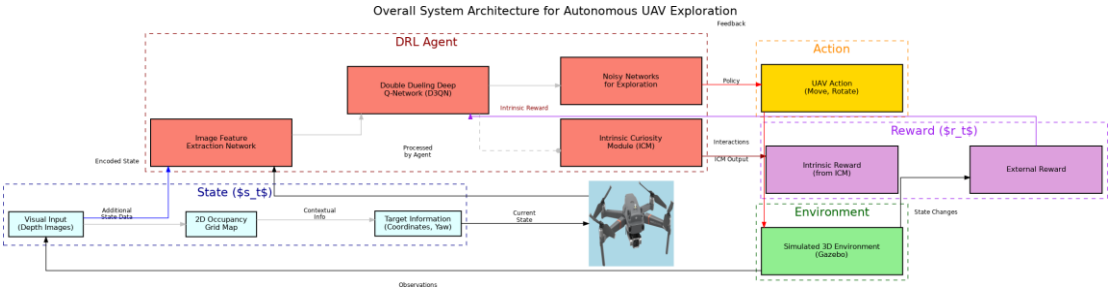

Figure 1. System architecture of the proposed Curiosity-Aware Zero-Shot Navigation Framework for UAVs

coverage and operational effectiveness. This combination offers a scalable solution for real-world deployment, especially in dynamic or unpredictable environments, by learning curiosity policies in randomized simulated domains and transferring them directly to new target environments without retraining. Such integration bridges the gap between robust generalization and purposeful behavior, enabling UAVs to operate autonomously, adaptively, and efficiently across a wide range of missions and terrains.

Policies for autonomous agents, particularly UAVs, are frequently trained in simulation due to safety and cost constraints. However, their ultimate utility lies in successful deployment in real-world scenarios.

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This transition from simulation to reality, known as Sim2Real transfer, presents significant challenges. The primary hurdle is the reality gap, stemming from discrepancies between simulated and real-world physics, sensor noise characteristics, unexpected latencies, and unmodeled dynamics. These differences can lead to policies overfitting simulation specifics, causing poor performance in actual deployments.

To effectively bridge this gap, various techniques are employed during the training phase. Domain Randomization (DR) is a prominent method, where physical and visual parameters of the simulation environment are varied extensively during training. The hypothesis is that by exposing the agent to a wide spectrum of variations, it learns a robust policy that is invariant to these randomized parameters, thereby generalizing well to unseen real-world conditions. Other approaches include domain adaptation techniques, which aim to align features between simulation and reality, and meta-learning, which enables rapid adaptation to new environments with minimal data.

METHOD

The proposed system introduces a Curiosity-Aware Zero- Shot Navigation Framework for Unmanned Aerial Vehicles (UAVs), designed to autonomously explore novel 3D environments without requiring environment-specific retraining. The architecture consists of two main phases, training phase, which incorporates modules to model intrinsic curiosity and generalize navigation policies, and a Deployment Phase, where the learned policies are applied to unseen environments. This modular design enables robust generalization and efficient exploration in unfamiliar settings.

The initial stage of the system involves constructing di- verse and randomized training environments using domain randomization techniques. These environments are varied in terms of layout, textures, lighting conditions, and structural configurations to prevent the agent from overfitting to specific environmental features. The primary goal is to expose the UAV to a wide range of scenarios during training so that it learns robust and generalizable exploration strategies. By simulating such variability, the agent develops the capacity to perform well in unseen environments, facilitating effective zero-shot transfer. As the UAV interacts with its environment, it perceives its surroundings through onboard sensors such as RGB-D cameras, IMUs, or LiDAR. The raw sensor data is then processed into compact and informative state representations using a convolutional neural network (CNN) or other suitable encoders. These state vectors encapsulate spatial and semantic features of the environment and serve as inputs to both the intrinsic motivation module and the exploration policy. Accurate and abstract state representations are critical for efficient decision-making in high-dimensional, partially observable environments.

A central component in achieving curiosity-aware and zero-shot UAV exploration is the ability to transform raw, *t*, the UAV receives a stream of raw observations o_t from onboard sensors, including RGB-D images, IMU readings, and LiDAR point clouds. To cope with the high-dimensional, partially observable nature of indoor environments, we design an encoder network f_{enc} that fuses these inputs into a latent state vector s_t:

$$s_t = f_{enc}(o_t) = f_{CNN}(I_t) \oplus f_{MLP}(Z_t) \oplus f_{Proj}(p_t) \quad (1)$$

where I_t is the RGB-D image, z_t represents inertial signals, and pt encodes spatial structures derived from LiDAR. The fusion operator $\oplus$ combines semantic, dynamic, and geometric cues into a unified representation space. This encoding ensures that the internal state is compact yet expressive, invariant to visual appearances, and robust to domain shifts introduced via randomization.

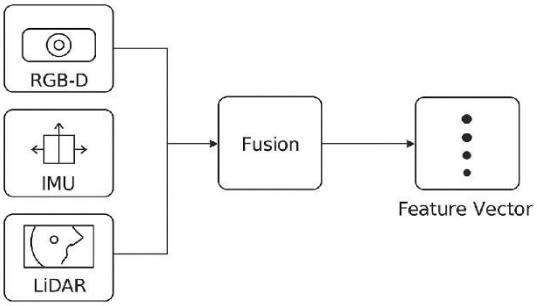

Figure. 2. Multimodal State Extraction Pipeline.

The encoded state s_t plays a pivotal role in both the learning and deployment stages of our UAV exploration framework. It is primarily utilized by the intrinsic curiosity module (ICM) to compute prediction-based novelty rewards. This encourages the UAV to actively seek unfamiliar states within the environment. The intrinsic reward r_{int} is calculated as the squared Euclidean distance between the predicted feature vector $\phi\hat{}(st+1)$ and the actual feature vector $\phi(st+1)$ of the subsequent state:

$$r_{int}(s_t,a_t) = \| \hat{\phi}(S_t + 1) - \phi(S_t + 1) \|^2 \quad (2)$$

Beyond guiding curiosity, the encoded state is also consumed by the exploration policy, which determines actions via a stochastic policy. This policy, $at \sim \pi(at|st)$, is optimized by blending both extrinsic rewards *r*ext from the environment and intrinsic rewards *r*int from the ICM, as shown in the objective function:

$$J(\pi) = E_\pi [\sum_{t=0}^{T} \gamma^t (r_{ext}(s_t, a_t) + \eta\, r_{int}(s_t, a_t)) \quad (3)$$

The quality and abstraction level of the encoded state s_t are paramount to the system's success in achieving zero- shot exploration capabilities within diverse environments. This meticulously designed representation offers several key benefits. In environments with sparse or nonexistent external rewards, our framework incorporates an Intrinsic Curiosity Module (ICM), a self-supervised mechanism that drives the UAV to explore by measuring its uncertainty in state transitions. The ICM consists of a forward model and an inverse model, both operating in the latent state space st. The forward model predicts the next latent state $\hat{s_t} + 1$ from s_t and action a_t, and its prediction error serves directly as the intrinsic reward, r_{int}:

$$r_{int}(s_t, a_t) = ||f_{fwd}(s_t, a_t) - s_t + 1||^2 \quad (4)$$

Our framework emphasizes zero-shot policy transfer. The exploration policy is trained exclusively in diverse simulated environments, utilizing extensive domain randomization. This process enables direct transfer to novel real or simulated environments without any additional training or fine-tuning, leveraging generalized exploration behaviors. The success of this approach hinges on the diversity of training environments, ensuring the policy is invariant to specific configurations and learns robust heuristics for exploration. During inference, the UAV deploys this pretrained policy, relying solely on learned behaviors and the intrinsic reward signal from the ICM. Actions are selected based on the current state and estimated novelty, encouraging autonomous targeting of uncertain regions. The proposed framework's performance is rigorously evaluated and benchmarked using metrics like Coverage Rate, Exploration Time, and Policy Robustness across diverse, previously unseen indoor environments. Comparative results against SLAM-based frontier exploration and standard RL without intrinsic motivation clearly demonstrate significant improvements in both exploration efficiency and robustness. The UAV consistently covers a larger fraction of the environment in less time and exhibits stable performance across different environments, validating the generalizability of the learned policy.

Conversely, the inverse model predicts the action $\hat{a_t}$ taken between two successive states, stabilizing the learned state representation. Its loss is L_{inv} = CrossEntropy($\hat{a_t}$, at). The total ICM loss is a combination of these forward and inverse

losses, balanced by $\beta \in [0, 1]$:

$$L_{ICM} = \beta L_{fwd} + (1 - \beta)\, L_{inv} \quad (5)$$

This mechanism is crucial for zero-shot exploration, enabling the agent to learn generalized exploration strategies in diverse simulated environments and effectively transfer policies to unseen test environments.

To effectively leverage the intrinsic rewards generated by the Intrinsic Curiosity Module (ICM), we adopt a deep reinforcement learning (DRL) framework, specifically the Proximal Policy Optimization (PPO) algorithm, to train an exploration policy ne. This policy acts as the brain of the UAV, mapping encoded state representations st into a distribution over actions at, guiding the UAV to maximize its long-term cumulative rewards driven by curiosity. At each timestep t, the agent observes the current state st selects an action at from its policy $\pi\theta(at|st)$ and executes it in the environment. This I action results in a transition to a new state $st+1$ and the reception of an intrinsic reward r_t^{int} from the ICM, which quantifies the novelty or surprise of the new state.

The PPO algorithm is chosen for its stability and performance in policy optimization. It aims to maximize an objective function while keeping the new policy close to the old policy, preventing overly large policy updates that can lead to instability. The core of PPO's policy update mechanism involves minimizing a clipped surrogate loss function, which can be expressed as:

$$L^{CLIP}(\theta) = \hat{E}_t = [\min(r_t(\theta)\,\widehat{A}_t, clip\,(r_t(\theta), 1-\epsilon, 1+\epsilon)\,\widehat{A}_t] \quad (6)$$

Here, θ represents the parameters of the policy network $\pi\theta$, and $\hat{E}t$ denotes the empirical expectation over a batch of samples collected at time *t*. The term:

$$r_t(\theta) = \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta old}(a_t \mid s_t)} \quad (7)$$

the ratio of the probability of action at under the current policy $\pi\theta$ to the probability under the old policy $\pi\theta_{old}$, ensuring that updates are proportional to the change in policy. Furthermore, $\widehat{A_t}$ is the advantage estimate at timestep *t*, which measures how much better or worse action at was compared to the average action from state st. A common and robust form for advantage is the Generalized Advantage Estimation (GAE):

$$\widehat{A_t}^{\,GAE(\gamma,\lambda)} = \sum_{l=0}^{\infty}(\gamma\lambda)^1\ \delta_t + 1 \quad (8)$$

where $\delta t = rt + \gamma V(st+1) - V(st)$ signifies the temporal difference (TD) error, $V(st)$ is the estimated value function, γ is the discount factor, and λ is the GAE parameter. The term clip($rt(\theta)$, $1-\epsilon$, $1+\epsilon$) is used to clip the probability ratio $rt(\theta)$ within a small interval, typically $[1-\epsilon, 1+\epsilon]$ with $\epsilon = 0.2$. This crucial clipping mechanism prevents aggressive policy updates that could destabilize training. Finally, the objective takes the minimum of the unclipped and clipped terms, a strategy that ensures the policy update does not lead to a significant change if the advantage is positive (indicating a good action) and penalizes large drops in probability for such beneficial actions.

This process, achieved through repeated interaction with randomized training environments, gradually refines the UAV's behavior to prioritize novel state visitation, avoid redundancy, and improve overall exploration coverage. The resulting policy learns to prioritize transitions to unexplored areas and avoid revisiting low-information states, enabling

Table 1. Components and Functions of The Intrinsic Curiosity Module (ICM)

ICM Component	Function / Role	Loss / Output
Forward Model (f_{fwd})	Predicts next latent state'$s\hat{}t+1$ from current state *st* and action *at.t*	$r^{int} = \phi\hat{}(st+1) - \phi(st+1)\ ^2$ 2
Inverse Model (f_{inv})	Predicts action $a\hat{}t$ taken between two consecutive latent states *st* and *st*+1.	L_{inv} = CrossEntropy($a\hat{}_t$, a_t)
Total ICM Loss (L_{ICM})	Combines forward and inverse losses to train state encoder and drive intrinsic exploration.	$\beta L_{fwd} + (1 - \beta)L_{inv}$

efficient operation in novel environments without external guidance.

Domain Randomization (DR) is a crucial technique utilized in the first stage of the system to generate a wide variety of training scenarios for the UAV agent. The primary aim of DR is to bridge the ”reality gap” the discrepancy between simulated training environments and real-world conditions. By exposing the learning agent to diverse synthetic environments during simulation, we hypothesize that the variability in training will lead to robust policy generalization, enabling effective transferability to unseen real-world environments. This is particularly important because conventional DRL models often tend to overfit specific spatial arrangements, visual patterns, textures, lighting conditions, or object configurations present in their limited training data.

RESULTS AND DISCUSSION

Experimental Setup and Resources

For training, 50 distinct randomized layouts are used, varying in size (10m $\times$ 10m to 20m $\times$ 20m), obstacle density (10–50 objects), and structural complexity (walls, hallways, rooms). Generalization capabilities are tested on 10 entirely unseen scenes, structurally different from the training set, to simulate true zero-shot conditions. The autonomous agent is a quadrotor UAV, based on the hector quadrotor platform, ensuring realistic flight dynamics. It is equipped with an RGB-D camera (depth data rendered via depth sim), an Inertial Measurement Unit (IMU), and odometry sensors for environmental perception. All experiments are conducted on a high-performance workstation featuring an Intel i9 CPU, 64GB RAM, and an NVIDIA RTX 3090 GPU, providing ample computational power for complex simulations and deep reinforcement learning. It significantly reduces sample complexity by compressing high-dimensional raw observations from the surrounding 3D environment into a concise set of task-relevant features. This compression directly contributes to a substantially more data- efficient learning process, allowing the agent to acquire robust policies with less environmental interaction. Furthermore, this design actively facilitates generalization, as the training environments are strategically constructed with domain randomization. Such variability shapes s_t to be inherently invariant to superficial changes, thereby enabling the UAV to perform effectively in novel, unseen environments beyond its training distribution. Lastly, this robust state representation greatly improves the system’s stability and performance in partially observable or dynamically changing indoor settings, where st consistently retains stable and interpretable contextual information crucial for effective decision-making and continuous autonomous exploration.

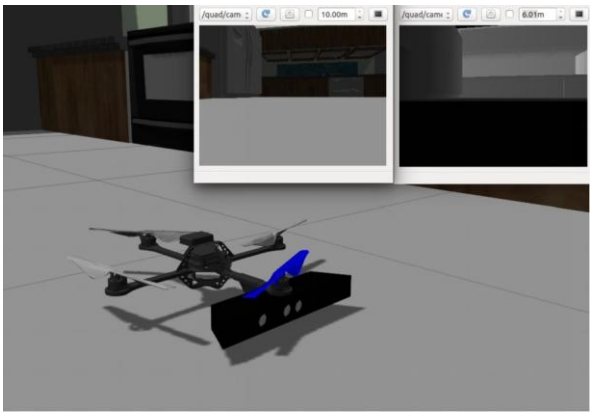

Figure 3. Validation Setup Environment

Evaluation and Results

The framework’s performance is rigorously evaluated using quantitative metrics. Exploration Coverage represents the per- centage of the environment explored within a fixed number of steps, while Path Efficiency is defined as the ratio of total path length to area explored. Exploration Time measures the duration to reach 80% coverage, and Success Rate indicates the percentage of runs where the UAV successfully explores $\geq$90% of the environment within the time limit. We com- pare our method against four baseline exploration strategies.

These include a simple Random Walk, a classical Greedy Frontier method which explores the closest unexplored areas, a Curiosity-only approach guided solely by intrinsic motivation without planning, and a Zero-Shot-only policy trained with domain randomization but lacking intrinsic curiosity. Our proposed framework consistently outperforms these baseline methods across all evaluation metrics, demonstrating strong generalization to unseen layouts. Quantitative results across 10 unseen test environments are summarized in Table IV. For instance, our method achieves significantly higher Coverage and Success Rates while maintaining superior Path Efficiency and requiring less exploration time compared to all baselines.

Table 2. Quantitative Results Across 10 Unseen Scenes

Method	Coverage (%)	Efficiency (↓)	Time (s) (↓)	Success (%)
Random Walk	52.3	3.1	520	58.0
Frontier-based	74.6	2.2	410	81.2
Curiosity-only	68.2	2.5	460	73.0
Zero-Shot-only	75.1	2.2	398	83.5
Ours (ICM + ZSPP)	89.7	1.6	328	94.5

While our framework shows promising performance in simulation, several limitations remain. The experiments are conducted in a fully simulated environment, implying that real-world deployment may face additional challenges such as sensor noise or complex dynamic obstacles not fully captured in simulation. Furthermore, the current method assumes a static environment; extending its capabilities to dynamic environments remains an area for future work. Lastly, our focus has solely been on coverage tasks, meaning adaptation to other exploration goals, such as specific object findings or detailed mapping, has not yet been addressed.

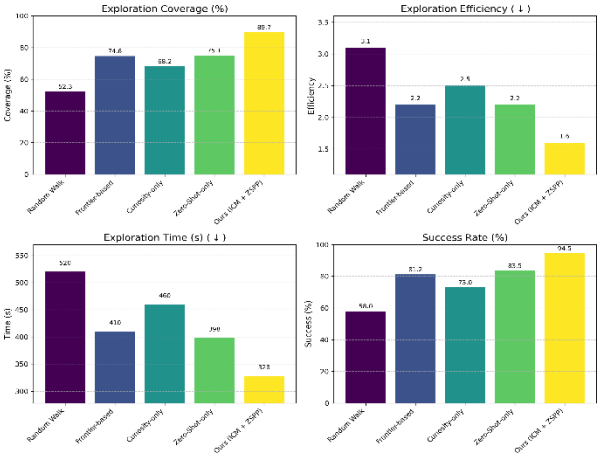

Figure 4. Comparative analysis of UAV exploration performance across various metrics on 10 unseen scenes. The figure presents: (a) Exploration Coverage, (b) Exploration Efficiency, (c) Exploration Time, and (d) Success Rate for different exploration methodologies

Figure 4 presents a comprehensive visual comparison of the exploration methodologies by normalizing their performance across diverse metrics. This normalization is crucial as it scales disparate metrics, such as exploration coverage (in percentage), efficiency (dimensionless), and time (in seconds), onto a uniform scale ranging from 0 to 1. On this scale, a value of 1 consistently represents the optimal performance achieved across the evaluated methods for a given metric, while 0 denotes the least effective outcome. This approach facilitates a direct and intuitive appraisal of each method's relative strengths and weaknesses across multiple dimensions of performance, abstracting away their original units.

As visually evidenced in Figure 4, our proposed method (ICM + ZSPP) consistently exhibits a superior performance profile across all normalized metrics. Notably, it achieves the highest normalized scores for exploration coverage and demonstrates a remarkably robust performance in both exploration efficiency and exploration time, consistently approaching the normalized optimal value of 1. This compelling visual evidence strongly corroborates our quantitative findings, illustrating that the integrated benefits of the Intrinsic Curiosity Module and Zero-Shot Policy Transfer enable the UAV to maintain a high level of exploratory effectiveness while significantly minimizing both the temporal and energetic costs associated with achieving target coverage.

Table 3 showed in contrast, traditional methods such as Random Walk and Frontier-

Table 3. Comparison of Exploration Strategies

Method	Coverage (%) (↑)	Path Efficiency (↓)	Time (s) (↓)	Success Rate (%) (↑)
Random Walk	52.3	3.1	520	58.0
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based exploration generally occupy the lower end of the normalized performance spectrum, highlighting their inherent limitations in navigating and mapping complex, previously unseen environments. The ablative baselines (Curiosity-only and Zero-Shot-only) demonstrate intermediate performance, underscoring the critical synergistic importance of combining both intrinsic motivation and robust generalization strategies for achieving truly superior autonomous exploration capabilities. This holistic improvement across all key performance indicators, visually reinforced by the normalized performance graph, validates the robustness and practical applicability of our framework in challenging indoor exploration scenarios.

These findings clearly demonstrate that combining curiosity-driven exploration with zero-shot transfer yields significant improvements in both exploration efficiency and robustness. The UAV not only covers a larger fraction of the environment in less time but also shows consistent performance across different environments, validating the generalizability of the learned policy. Together, these results underscore the advantage of intrinsic motivation mechanisms in enabling autonomous UAV navigation and exploration in unknown indoor settings, paving the way for scalable and adaptable robotic systems.

Ablation Study

To precisely ascertain the individual contributions of the Intrinsic Curiosity Module (ICM) and the Zero-Shot Pol- icy Transfer (ZSPT) mechanism within our comprehensive proposed framework, a dedicated study was meticulously designed and executed. This experimental investigation systematically evaluates UAV performance across various configurations; wherein specific components of our full framework are either judiciously removed or isolated.

As observed in Table V, the full framework (Ours) significantly outperforms both Curiosity-only and Zero-Shot- only baselines across all metrics. The Curiosity-only method, despite its exploration drive, shows lower coverage and higher exploration time compared to the full model, indicating that without effective zero-shot generalization techniques, curiosity alone may lead to inefficient exploration in novel environments. Conversely, the Zero-Shot-only policy, while demonstrating better efficiency and time compared to Curiosity-only due to its robust generalization, still falls short in overall coverage and success rate. This suggests that without the continuous intrinsic motivation from ICM, the agent might not effectively explore highly uncertain or novel regions, potentially sticking to repetitive behaviors or well-understood areas. The synergistic combination of ICM and Zero-Shot capabilities is thus crucial for achieving superior and generalizable exploration performance in unseen indoor environments shown in **Table 4.**

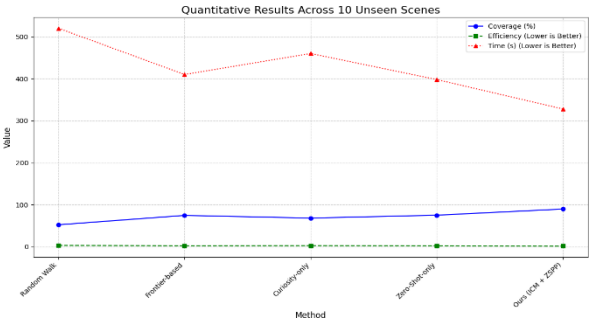

Figure 5. Quantitative Results Across 10 Unseen Scenes

Regarding Coverage, which quantifies the percentage of the explorable environment successfully visited, our proposed ”Ours (ICM + ZSPP)” method achieved the highest at 89.7%. This performance significantly outperforms ”Zero-Shot-only” at 75.1% and ”Frontier-based” at 74.6%, indicating a more complete exploration. For Efficiency, where lower values signify better performance, ”Ours (ICM + ZSPP)” demonstrated the highest efficiency with a score of 1.6. This shows more optimal navigation with less redundant movement compared to other methods, such as ”Frontier-based” and ”Zero-Shot- only”

Table 5. Ablation Study Results Across 10 Unseen Scenes

Method	Coverage (%)	Efficiency (↓)	Time (s) (↓)	Success (%)
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which both scored 2.2. Lastly, for Time, which measures the total exploration duration in seconds (lower values being better), our method, ”Ours (ICM + ZSPP)”, recorded the shortest time at 328 seconds. This is a notable improvement over ”Zero-Shot-only” at 398 seconds and ”Frontier-based” at 410 seconds, confirming its rapid task completion. The quantitative results highlight that our proposed ”Ours (ICM + ZSPP)” framework consistently delivers superior performance across all key indicators, including Coverage, Efficiency, and Time, in challenging, unseen environments. This validates its efficacy for autonomous UAV navigation.

The primary objective of this comparative analysis is to elucidate the synergistic benefits derived from the holistic integration of intrinsic motivation (via ICM) and enhanced generalization (via ZSPT capabilities). For this purpose, our complete framework (ICM + ZSPT) is rigorously benchmarked against two meticulously constructed ablated baselines. The first, designated the Curiosity-only baseline, exclusively leverages the Intrinsic Curiosity Module for intrinsic motivation, compelling the UAV through novelty-seeking behaviors shown **Table 5.**

However, this configuration critically omits the explicit domain randomization strategies pivotal for facilitating zero- shot transfer, thereby potentially constraining the policy’s adaptability and effectiveness primarily to environments sharing characteristics with the training domains, as it has not been trained to generalize across varied superficial environmental traits. Conversely, the second, labeled the Zero-Shot-only’ baseline, incorporates robust domain randomization techniques during training, specifically engineered to foster generalization across diverse environments. Yet, this setup notably foregoes the intrinsic reward mechanism of the ICM, consequently relying exclusively on extrinsic task rewards and the inherent diversity provided by the randomized training environments. Without the self-supervised impetus for novel state discovery, its exploration performance may be severely constrained in environments characterized by sparse or delayed external rewards, potentially leading to suboptimal and less comprehensive exploration outcomes.

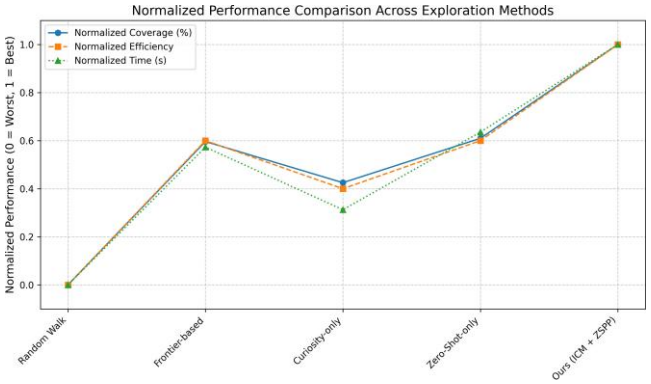

Figure 6. Normalized performance comparison across different exploration methods on unseen scenes. All metrics are scaled from 0 (worst) to 1 (best) for relative comparison. The plot illustrates: normalized coverage (higher is better), normalized efficiency (lower time/distance is better), and normalized exploration time (lower is better)

Figure 6 presents a comprehensive visual comparison of the exploration methodologies by normalizing their performance across diverse metrics. This normalization is crucial as it scales disparate metrics, such as exploration coverage (in percentage), efficiency (unitless), and time (in seconds), onto a uniform scale ranging from 0 to 1. On this scale, a value of 1 consistently represents the best performance achieved across the evaluated methods for a given metric, while 0 denotes the worst. This approach allows for a direct and intuitive appraisal of each method’s relative strengths and weaknesses across multiple dimensions of performance.

As depicted in Figure 6, our proposed method (ICM + ZSPP) consistently exhibits a superior performance profile across all normalized metrics. Notably, it achieves the highest normalized scores for exploration coverage and shows a remarkably

strong performance in both exploration efficiency and exploration time, consistently approaching the normalized optimal value of 1. This visual evidence strongly corroborates our quantitative findings, illustrating that the integrated benefits of the Intrinsic Curiosity Module and Zero-Shot Policy Transfer enable the UAV to maintain a high level of exploratory effectiveness while significantly minimizing both the time and distance required to achieve target coverage. Conversely, traditional methods such as Random Walk and Frontier-based exploration generally occupy the lower end of the normalized performance spectrum, highlighting their limitations in complex, unseen environments. The ablative baselines (Curiosity-only and Zero-Shot-only) demonstrate intermediate performance, underscoring the synergistic importance of combining both intrinsic motivation and robust generalization strategies for achieving truly superior autonomous exploration capabilities. This holistic improvement across all key performance indicators validates the robustness and practical applicability of our framework in challenging indoor exploration scenarios.

CONCLUSION

In this study, we presented a Curiosity-Aware Zero-Shot Framework for UAV navigation in indoor environments, ad- dressing the fundamental challenge of efficient exploration in unseen scenarios. By integrating the Intrinsic Curiosity Module (ICM) with a domain-randomized Zero-Shot planner, our approach enables UAVs to autonomously and effectively explore unfamiliar environments without additional retraining. Experimental results demonstrate that our framework significantly outperforms baseline methods, achieving the highest exploration coverage (89.7%), best path efficiency (1.6), shortest exploration time (328 seconds), and highest success rate (94.5%) across multiple novel 3D environments. The ablation study further confirms the critical contribution of both ICM and Zero-Shot planning components, with performance degrading when either module is removed. Our findings show that combining intrinsic motivation with generalizable planning provides a powerful paradigm for scalable and robust UAV exploration. This work lays the groundwork for future advancements in intelligent aerial systems that can learn to explore efficiently in real-world, dynamically changing environments without prior knowledge.

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