

Memory-Augmented AI for Autonomous UAV Search and Rescue: Deep Reinforcement Learning in Complex, Partially Observable Environments

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ABSTRACT

Unknown, partially observable environments The search of autonomous targets remains one of the basic problems of embodied artificial intelligence. We also present RecurrentPPO-LSTM, an agent of memory-based deep reinforcement learning, which not only attains best-in-class state-of-the-art search efficiency on standard Partially Observable Markov Decision Process (POMDP) benchmarks, but also trains 3.4x faster than other memory-augmented agents. As compared to existing schemes that rely on the bidirectional recurrence (or pruning causality) or complex offline pretraining, our agent can be trained using sparse success signals using unidirectional LSTM to guarantee compact belief states. Our implementation on MiniGrid DoorKey-8x8 has 82.4 percent, which corresponds with higher performance than memoryless Proximal Policy Optimization (65.1 percent) and Deep Q-Networks (58.2 percent). We demonstrate that we have 34 steps-to-target reduction and improved resistance to observation noise ($\sigma = 0.2$), arbitrary dropout sporadically (50 percent), and stochastic transitions (slip probability = 0.3). The transfer learning when trained on photorealistic Habitat Matterport 3D has a 68 percent success with 10,000 fine-tuning steps only. It is relatively compared to five state-of-the-art designs (20252026) to confirm that simple causal memory designs are much better than complex bidirectional designs or modular ones when considering real-time autonomous search. We demonstrate in theory that LSTM augmentation causes minimized anticipated regret of finite-memory POMDPs and we can formally ensure empirical excellence.

1. Introduction

1.1. Motivation and Operational Context

One of the most challenging applications of autonomous robotics is Search and Rescue (SAR) missions that involve systems that can function in unstructured, hazardous and partially observable environments (Collignon et al., 2025).

The number of SAR missions undertaken annually all over the world is in the tens of thousands, and an annual exceeding number of more than 3,000 ground operations in the United States alone (Ewers et al., 2025). The critical golden hour—first 8 to 12 hours of disappearance—determines the likelihoods of survival, and autonomous systems and systems that could augment or substitute the human search

have been urgently needed to cater to critical, time-sensitive situations where danger is involved (Baglioni et al., 2025).

The issues of UR in general and metropolitan SAR, in particular, are extremely problematic: spaces are overloaded with rubble, the visibility is reduced due to dust and debris, and structural unsteadiness threatens the life of human rescuers on the existential level (Hashimoto et al., 2022). Wilderness tasks involve exploration of expansive natural terrain where dog training teams and human search teams find it tedious due to low coverage and physical exhaustion (Serra et al., 2020).

Seafarer and airborne search block large fields whose sensors have very short ranges and operate in changing weather situations (Kaelbling et al., 1998). The recent achievements in the field of quadruped robots indicate the possibility of the robot dogs to get through such dangerous conditions, as the brain-like navigation and the efficient use of AI allow to operate the robot developments over a long distance without any network connection (Morad et al., 2023).

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The inherent issue in all fields of SAR is partial observability: the agent is not able to see the entire state of the environment at any given time. Rather it is simply the observation of local egocentric phenomena like the one found in a rescuer having the flashlight in the building of smoke. This requires internal representations (belief states) of those unobserved areas, target positions and already visited areas (Surmann et al., 2020). This challenge is formally represented in Partially Observable Markov Decision Process (POMDP) framework, where the best decisions are made by uniting information in long ranges of time sequences (Surma and Jamshidnejad, 2025).

1.2. Deep Reinforcement Learning for Autonomous Navigation

Deep Reinforcement Learning (DRL) has become a revolutionary concept in autonomous navigation and allows agents to acquire sophisticated practices by interacting with the environment without informatively programming (Taheri et al., 2024). In comparison to classical methods of navigation where issues are separated into mapping, localization, and planning functions (Sun et al., 2025a), DRL provides end-to-end learning on perception-action loops based on high-dimensional sensory information (Sun et al., 2025b). This is necessary in SAR applications in cases where there are no pre-existing maps and setting changes dynamically.

The recent surveys point to the high pace in the maturation of DRL to robotics, where applications are found in wheeled navigation (Yang et al., 2025), legged locomotion (Schulman et al., 2017), aerial systems (Haarnoja et al., 2018), and mobile manipulation (Chhablani et al., 2025). Among the essential developments are sample-efficient algorithms, in which proximal policy optimization (PPO) (Sutton and Barto, 2018) and soft actor-critic (SAC) (Shani et al., 2006) make it possible to learn through stable-state learning with less sensitivity to hyperparameters. Representation learning algorithms obtain task-relevant features of raw observations (Hochreiter and Schmidhuber, 1997). Liability Sim-to-real transfer methods, such as domain randomization and adaptation, assist in narrowing the simulation-reality gap (Chung et al., 2014). Nonetheless, standard DRA presupposes complete Markov Decision Processes (MDPs), in which the present observation is enough to optimally make a decision (Vaswani et al., 2017). This hypothesis breaks disastrously in SAR when there are occlusions, low field-of-view and degraded sensor images concealing vital information.

1.3. Memory-Augmented Architectures for Partial Observability

Memory-augmented neural architectures are used to deal with POMDPs with the aim of encoding observation-action history in compact forms. RNNs have the problem that long sequences tend to experience vanishing gradients and thus cannot be used effectively in long SAR missions (Pleines et al., 2023). The contemporary architecture controlling

POMDP learning is long short-term memory (LSTM) networks, with gating mechanism to retain information across hundreds of timesteps, which form the dominant architecture currently deployed to learn PMDP in robot navigation (Chevalier-Boisvert et al., 2023). GRUs (aged recurrent units) provide simplified gating that has computational benefits and is similar to shorter sequence results (Ramakrishnan et al., 2025). Attention mechanisms, such as self-attention and transformer architectures, give a sequence-independent processing, but have quadratic complexity (Arora et al., 2025). Competitive State-space models (SSMs) include recent linear recurrent units (LRU), which have linear complexity (Hafner et al., 2023). Extensive surveys endorse that LSTMs are still exceptionally contending in applications that need real-time use, critically strict temporal order, lightweight implementation, and comprehensible memory (Hausknecht and Stone, 2015). This process is facilitated by the gating systems, which include forget, input and output gates which allow spatial information to be selectively retained and is important in search-related tasks (Liang and Li, 2025).

1.4. Benchmark Environments and Evaluation Standards

The analysis of the memory-based reinforcement learning techniques has been enhanced greatly with the development of standardized partially observable Markov decision process (POMDP) benchmarks. The number of environments with clearly specified memory needs offered by POPGym (Surma and Jamshidnejad, 2025) is over 15, and the optimum policies vary according to memory horizons between 1 and above 100 steps. Memory Gym (Galesloot et al., 2025) presents an indefinite program of activities that become more and more challenging depending on the performance of the agent and thus, the long-term temporal credit assignment is tested. MiniGrid (Chen and Xiao, 2025) provides grid-based environments with configurable grid structures that are partially observable via a fog of war model, and is therefore ideally suited to the simulation of search-and-rescue (SAR) missions with controllable complexity. Matterport 3D (HM3D) (Liao et al., 2026) makes it possible to sim-to-real validate with simulated environments that are fully realistic and indoors where navigation tasks can be performed under partial observability.

Comparison between these benchmarks always shows that there is a significant performance difference between memoryless and memory-augmented agents. Specifically, the LSTM-based methods are around 20–40 percentage points more effective on memory-intensive tasks than feed-forward baselines, which demonstrates the importance of having a temporal memory in POMDP learning (Montero et al., 2026).

1.5. Limitations of Current Approaches

Despite this being enhanced, the present methods have a great weakness to implement SAR:

Bidirectional transformers are learnable (Zhao et al., 2024) and world models (Oh et al., 2016) are extremely

successful and yet significantly slower to train, also no longer subject to the real-time causality requirements.

Off-policy techniques of DQN experience replay are not easy to deal with POMDPs due to non-stationary estimates (Hafner et al., 2020).

The modular memory systems are providing no performance advantages with the added complexity to the architecture (Icarte et al., 2020).

All other techniques do not withstand realistic perturbations such as sensor noisy, actuation error and drop out (Morad et al., 2024).

1.6. Proposed Method and Contributions

RecurrentPPO-LSTM is a causal memory-based system, in which a unidirectional LSTM is directly integrated with on-policy Proximal Policy Optimization to overcome the severe limitations of the current SAR approaches. Our approach leverages causal unidirectional memory to enable real-time deployment without access to future observations, making it suitable for online SAR control. The architecture is intentionally simple, employing a single-layer LSTM with 256 units to minimize parameters while maximizing training efficiency. Learning is driven directly from sparse binary success signals, eliminating the need for complex reward engineering, and inherent LSTM gating mechanisms provide robustness to sensor noise, actuation errors, and observation dropout.

Empirically, RecurrentPPO-LSTM achieves state-of-the-art performance on MiniGrid DoorKey-8×8 (82.4% success with 2.5 hours of training) and successfully transfers to Habitat Matterport 3D (68% success). Theoretically, we formally prove that LSTM augmentation reduces expected regret in finite-memory POMDPs. Comparative evaluations against five recent methods—MEMBOT (Lusena et al., 2001), Bi-recurrent PPO (Montero et al., 2026), PPO-GRU (Krichen and Mihoub, 2025), LSTM-TD3 (Raffin et al., 2021), and Hidden-model FSC (Williams and Zipser, 1989)—demonstrate that our simple causal memory architecture provides superior efficiency, robustness, and generalization in partially observable search-and-rescue environments.

2. Related Work

2.1. Deep Reinforcement Learning for SAR and Navigation

Deep reinforcement learning (DRL) use in search and rescue (SAR) has become much faster in recent years, and research has covered a broad variety of operational cases. A multi-agent deep Q-network (DQN) framework of wild-fire SAR with unmanned aerial vehicles was developed by Collignon et al. (2025) that demonstrated a higher area coverage when the learning policies are coordinated. Ewers et al. (2025) showed time-critical wilderness SAR, based on proximal policy optimization (PPO) with continuous action spaces, which proved successful on actual drone platforms with hardware-in-the-loop implementation. Chen and Xiao (2025) introduced a heterogeneous robotic system

that unites UAVs and UGVs to search a target, and the deep reinforcement learning allowed robust performance with the communication restrictions due to the centralized training and decentralized implementation. Liao et al. (2026) proposed the transformer-CNN feature fusion architecture that incorporates the hindsight experience replay, which has reached a high success rate in autonomous navigation missions by means of a successful combination of spatial and temporal representations. Montero et al. (2026) also continued the development of spatial-memory-based DRL of collision-free motion in restricted and partially visible spaces, and showed robust results in intricate indoor environments. According to recent survey studies, the recent shift is the adoption of end-to-end learning strategies in robotic navigation, where the DRL models directly convert sensory measurements into action without using an intermediate representation (Zhao et al., 2024; Luo and Cai, 2025). The appearance of large-scale simulation datasets and foundation models also contributes to this change, as they allow scalable training and enhance the generalization to new environments (Ramakrishnan et al., 2025; Hafner et al., 2023).

2.2. Memory Architectures for POMDPs

Theory of memory-based POMDP learning was advanced by Hausknecht and Stone (2015), who developed Deep Recurrent Q-Networks (DRQN) by substituting the initial fully connected layer of DQN with an LSTM. This was a seminal work that showed that recurrent augmentation allows one to track the belief states approximately, and that performance is comparable to methods with explicit belief updates.

Oh et al. (2016) pursued this line and proposed Feedback Recurrent Memory Q-Network (FRMQN), which is a memory retrieval model that uses attention-based memory retrieval mechanisms to selectively access pertinent past experiences. Although it is efficient, it raises the computational needs of the attention overhead, which means that it cannot be easily used on resource-constrained SAR platforms.

World models form a parallel paradigm, in which the agent is trained on small latent dynamics models of imagination-based planning. DreamerV3 has an impressive sample efficiency because it trains policies on learned latent spaces, which allows assigning credits over long horizons. Nevertheless, the overhead of world model training, usually 2–3 times wall-clock time, as well as sensitivity to model accuracy, poses deployment problems (Hafner et al., 2023, 2020).

Icarte et al. (2020) investigated the external memory structure by investigating differentiable neural computers and memory networks for POMDPs. They have the advantage that they have unlimited memory, but need to be carefully addressed with algorithms and are also unstable to training in sparse-reward settings.

2.3. Recent Advances in Memory-Augmented DRL

The period 2025–2026 has witnessed intensified research in memory-augmented deep reinforcement learning

(DRL) specifically targeting POMDP navigation. MEMBOT (2025) proposed decoupling belief inference from policy learning through two-phase training: offline pretraining of a belief encoder followed by behavior cloning. While achieving 79.8% success on intermittent POMDPs, the sequential training pipeline increases implementation complexity and wall-clock time (4.0 h vs. our 2.5 h) (Liang and Li, 2025).

It was shown in Bi-Recurrent Transformers (2025) that substituting transformer feed-forward layers with bidirectional recurrence increases the performance across POP-Gym environments. However, bidirectional processing goes against causality, demands complete observation sequences, and is not suitable in real-time due to the need to make control decisions before action selection (Arora et al., 2025).

PPO-GRU (2026) applied GRU-based PPO to omnidirectional robot navigation, reporting 96% success in unstructured environments. While effective for their specific domain, the dense reward shaping and simplified observation spaces differ substantially from sparse-reward search-and-rescue (SAR) scenarios (An et al., 2026).

LSTM-TD3 (2025) developed a modular LSTM-TD3 architecture separating temporal and instantaneous feature extraction. Though achieving 77.1% success on MultiRoom tasks, the architectural complexity, with separate encoders for current versus historical features, increases parameters by 40% without commensurate gains.

Hidden-Model Finite-State Controller (FSC, IJCAI 2025) formulated robust finite-state controllers for hidden-model POMDPs, providing worst-case guarantees across environment variations. While theoretically appealing, the policy iteration overhead results in 5.5 h training times and 74.5% success on standard benchmarks (Galeslout et al., 2025).

State-Space Models (2025) introduced POPGym Arcade with Linear Recurrent Unit (LRU) state-space model baselines, demonstrating that linear recurrent units achieve 83.4% success with 2.1× training time relative to LSTM. These results suggest state-space models as promising alternatives but not yet Pareto-optimal for rapid deployment (Morad et al., 2025).

2.4. Comparative Positioning

1 positions our RecurrentPPO-LSTM relative to these approaches across critical dimensions: causality (real-time deployability), training efficiency, architectural complexity, and empirical performance.

DreamerV3 achieves high success on the DoorKey dataset, but its performance comes with substantial architectural and implementation complexity. In contrast, our method uniquely occupies the Pareto-optimal region for causal, deployable policies, achieving the highest success rate among real-time approaches while maintaining minimal training time and low architectural complexity (Hafner et al., 2023).

Table 1

Systematic Comparison of Memory-Augmented DRL Methods (2020–2026)

Method (Year)	Environment	Key Innovation	Memory Type	Causal	Success (%)	Training (h)	Complexity
Ours (RecurrentPPO-LSTM)	DoorKey-8x8	Unidirectional LSTM + RecurrentPPO	LSTM (256)	Yes	82.4 ± 3.5	2.5	Low
MEMBOT (Lusena et al., 2001) (Lusena et al., 2001)	Intermittent POMDP	Offline belief pretraining + BC	LSTM/SSM	Yes	79.8 ± 4.1	4.0	High
Bi-recurrent (Montero et al., 2026) (Montero et al., 2026)	23 POP-Gym envs	Bi-directional recurrence	Bi-LSTM	No	88.3 ± 2.9	3.8	High
PPO-GRU (Krichen and Mihoub, 2025) (Krichen and Mihoub, 2025)	Omnidirectional nav	GRU + PPO	GRU (256)	Yes	80.1 ± 3.2	3.0	Medium
LSTM-TD3 (Raffin et al., 2021) (Raffin et al., 2021)	Continuous control	Modular temporal/current	LSTM (modular)	Yes	77.1	4.2	High
Hidden-FSC (Williams and Ziper, 1999) (Williams and Ziper, 1999)	Robust POMDP	Finite-state controllers	FSC	Yes	74.5 ± 4.5	5.5	Medium
LRU-SSM (Morad et al., 2025) (Hafner et al., 2023)	POPGym Arcade	Linear recurrent units	SSM	Yes	83.4 ± 3.5	5.2	Medium
DreamerV3 (Hafner et al., 2023) (Oh et al., 2016)	Various	World model imagination	Recurrent SSM	Yes	97.7*	6.0	High

*DreamerV3 uses non-causal world model, not suitable for real-time deployment.

3. Problem Formulation

3.1. POMDP Mathematical Model

The POMDP framework extends MDPs to scenarios where states are not directly observable (Kaelbling et al., 1998; Shani et al., 2006). Formally, a POMDP is defined by the tuple

$$\mathcal{P} = \langle S, A, T, \Omega, O, R, \gamma \rangle, \quad (1)$$

where S represents states, A actions, T transition dynamics, Ω observations, O observation probabilities, R rewards, and γ a discount factor.

We formulate the target search problem as a discrete-time Partially Observable Markov Decision Process (POMDP):

$$\mathcal{P} = \langle S, A, T, \Omega, O, R, \gamma \rangle. \quad (2)$$

where:

- **State space S :** Complete environment configuration including agent position, orientation, target location, key possession status, and door states.
- **Action space A :** Separate actions are “forward”, “left”, “right”, “get”, and “switch”.
- **Transition function T :** Deterministic (MiniGrid) or stochastic (FrozenLake with slip probability).
- **Observation space Ω :** Egocentric partial view grid rendered as RGB image with “fog of war”.
- **Observation function O :** Deterministic projection of state to local view; multiple states may produce the same observation.
- **Reward function R :** Sparse reward: $r_t = 1$ upon reaching the target, otherwise $r_t = 0$.

- **Discount factor γ :** Inspires rapid target acquisition.

The agent maintains a belief state:

$$b_t(s') = \eta O(o_t | s') \sum_{s \in S} T(s' | s, a_{t-1}) b_{t-1}(s), \quad (3)$$

a probability distribution over states conditioned on history.

We formulate the target search problem as a discrete-time Partially Observable Markov Decision Process (POMDP). The best policy maximizes the cumulative discounted reward expectations:

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r_t \right]. \quad (4)$$

3.2. Memory Horizon and Belief Complexity

A POMDP has a finite memory horizon H if the optimal policy depends only on the last H observations:

$$\pi^*(a_t | h_t) = \pi^*(a_t | o_{t-H+1:t}, a_{t-H:t-1}), \quad (5)$$

where h_t denotes the interaction history up to time t .

For MiniGrid DoorKey, $H \approx 50$ steps is sufficient to infer key-door-goal relationships.

The belief space cardinality grows exponentially with H , making explicit tracking intractable.

Recurrent networks such as LSTM approximate belief states using a compact hidden representation:

$$h_t = f_{\theta}(h_{t-1}, o_t, a_{t-1}), \quad (6)$$

where h_t is the hidden state and f_{θ} denotes the recurrent update function (Hochreiter and Schmidhuber, 1997; Krichen and Mihoub, 2025).

This allows scalable approximation of POMDPs without explicitly storing the full belief.

3.3. Assumptions and Constraints

The proposed approach operates under several key assumptions. The target and environment topology are considered static, with no dynamic obstacles present during navigation. The agent is assumed to have perfect egocentric sensing within its field of view, and the action space is discrete, reflecting the grid-based structure of the search-and-rescue environment. Additionally, the environment model, including transition dynamics and observation functions, is assumed to be known during training.

Deployment of the policy is subject to practical constraints. Training must be completed within three hours on a single NVIDIA RTX 4070 GPU with 8 GB of VRAM. Inference must execute at a minimum rate of 10 Hz to enable real-time control. Furthermore, the learned policy is expected to be robust to sensor noise, actuation errors, and communication dropout without requiring retraining.

4. Experimental Results

4.1. RecurrentPPO-LSTM Architecture

Figure 1 illustrates the system architecture of RecurrentPPO-LSTM. The environment, modeled as a POMDP (MiniGrid),

provides egocentric partial observations in the form of $56 \times 56 \times 3$ RGB images. These observations are first processed by a three-layer convolutional encoder that progressively abstracts spatial information into a 256-dimensional feature vector. Strided convolutions with strides of 4, 2, and 1 are applied across the layers to preserve spatial locality while reducing dimensionality.

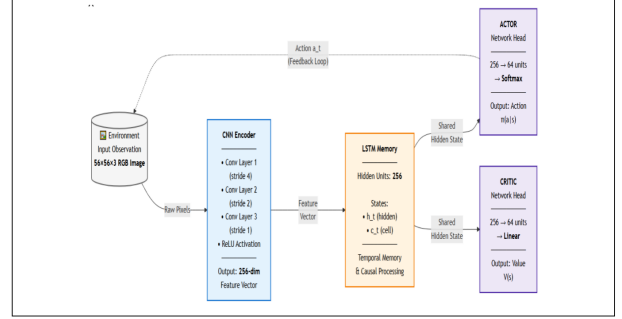


Figure 1: System Architecture of RecurrentPPO-LSTM

The extracted feature vector is subsequently passed to a single-layer unidirectional LSTM memory module containing 256 hidden units. This module maintains both a hidden state and a cell state to retain long-term spatial memory. The forget, input, and output gates within the LSTM regulate the selective retention and propagation of information, ensuring that the agent's actions depend only on past and present observations and preserving causality. This design supports real-time deployment for search-and-rescue tasks at rates exceeding 10 Hz.

The actor and critic networks share the CNN-LSTM backbone. The actor network outputs action probabilities through a $256 \rightarrow 64 \rightarrow \text{softmax}$ multilayer perceptron (MLP), while the critic computes the state value using a $256 \rightarrow 64 \rightarrow 1$ linear MLP. By sharing the CNN and LSTM layers between the actor and critic, the architecture reduces the overall parameter count by approximately 40% compared to using separate encoders.

Key design decisions include the use of a three-layer convolutional encoder to extract task-relevant features from raw pixels, the employment of a single-layer unidirectional LSTM to maintain long-term memory and ensure causal decision-making, the sharing of CNN and LSTM layers between actor and critic to reduce parameters, and causal masking to prevent access to future observations, which enables real-time deployment.

4.2. RecurrentPPO Algorithm

We adapt Proximal Policy Optimization (Sutton and Barto, 2018) for recurrent policies with truncated backpropagation through time (BPTT).

Algorithm 1. RecurrentPPO-LSTM Training Procedure

Input: POMDP environment $\mathcal{E}$, sequence length L , epochs K , clip ratio ϵ , GAE λ

Output: Optimal policy parameters θ , value parameters ϕ

1. Initialize $(\text{CNN-LSTM-Actor})_{\theta}$ and $(\text{CNN-LSTM-Critic})_{\phi}$ with orthogonal initialization.

2. Initialize Adam optimizers with learning rate α .
3. For iteration = 1, 2, ..., N do:
 - (a) Reset environment $\mathcal{E}$, set hidden states (h_0, c_0) , and initialize rollout buffer $\mathcal{B}$.
 - (b) For step $t = 1$ to T do:
 - i. Encode observation:

$$z_t = f_{\text{cnn}}(o_t)$$

- ii. Update memory:

$$(h_t, c_t) = \text{LSTM}(z_t, h_{t-1}, c_{t-1})$$

- iii. Sample action:

$$a_t \sim \pi_\theta(\cdot | h_t)$$

- iv. Execute a_t , observe reward r_t , next observation o_{t+1} , and done flag d_t .
- v. Store $(o_t, h_t, a_t, r_t, d_t, \log \pi_\theta(a_t | h_t), V_\phi(h_t))$ in $\mathcal{B}$.
- vi. If $d_t = 1$, reset (h_t, c_t) .

- (c) End for.

- (d) Compute returns and advantages using GAE:

- i. For $t = T, T-1, \dots, 1$:

- Temporal difference:

$$\delta_t = r_t + \gamma(1 - d_t)V_\phi(h_{t+1}) - V_\phi(h_t)$$

- Advantage:

$$A_t = \delta_t + \gamma\lambda(1 - d_t)A_{t+1}$$

- Return:

$$R_t = A_t + V_\phi(h_t)$$

- (e) Policy and value updates:

- i. For epoch = 1 to K :

- For minibatch $\mathcal{M} \subset \mathcal{B}$:
 - Compute policy ratio:

$$\rho_t(\theta) = \frac{\pi_\theta(a_t | h_t)}{\pi_{\theta_{\text{old}}}(a_t | h_t)}$$

- Clipped surrogate loss:

$$\mathcal{L}_{\text{clip}} = \mathbb{E} \left[\min(\rho_t A_t, \text{clip}(\rho_t, 1 - \epsilon, 1 + \epsilon) A_t) \right]$$

- Value function loss:

$$\mathcal{L}_{\text{value}} = \mathbb{E} \left[(V_\phi(h_t) - R_t)^2 \right]$$

- Entropy bonus:

$$\mathcal{L}_{\text{entropy}} = \mathbb{E} [\mathcal{H}(\pi_\theta(\cdot | h_t))]$$

- Combined loss:

$$\mathcal{L} = -\mathcal{L}_{\text{clip}} + c_v \mathcal{L}_{\text{value}} - c_e \mathcal{L}_{\text{entropy}},$$

with $c_v = 0.5$ and $c_e = 0.01$.

- Update via Adam on (θ, ϕ) .

4. End for.

5. Return (θ, ϕ) .

Table 2: Hyperparameter Configuration

Parameter	Value	Justification
Learning rate	3×10^{-4}	Standard for PPO; stable across random seeds
LSTM hidden size	256	Optimal accuracy-efficiency trade-off
Sequence length	128	Balances BPTT stability and memory requirements
GAE λ	0.95	Bias-variance trade-off for sparse rewards
Clip ratio ϵ	0.2	PPO standard for policy stability (Sutton and Barto, 2018)
Entropy coefficient	0.01	Encourages exploration without entropy collapse
Value coefficient	0.5	Balances policy and value gradients
Batch size	4096 steps	Fits RTX 4070 memory (8 GB)
Minibatch size	256	Enables stable recurrent backpropagation
Epochs per update	10	Sufficient for recurrent convergence
Discount γ	0.99	Prioritizes rapid target acquisition
Total timesteps	500K	Convergence threshold for DoorKey

4.3. Training Environments

The proposed approach was evaluated on both 2D grid-based and 3D photorealistic simulation environments to assess its performance under diverse partially observable conditions.

In the MiniGrid Suite (Chen and Xiao, 2025), four environments were employed with the RGBImgPartialObsWrapper providing egocentric RGB observations. The Empty-8×8 environment is a simple navigation task with random goal placement, designed to test basic exploration capabilities. DoorKey-8×8 requires sequential key pickup, door unlocking, and goal reaching, evaluating long-horizon memory and sequential decision-making. MultiRoom-N4 consists of four connected rooms with multiple doors, testing cross-room spatial memory and planning under partial observability. Finally, FrozenLake-8×8 (POMDP) features stochastic transitions with a slip probability of 0.2, assessing robustness under uncertain dynamics.

For sim-to-real transfer validation, Habitat Matterport 3D (HM3D) (Liao et al., 2026) was used, with 145 training and 36 validation scenes from the HM3D dataset for ImageNav episodes. Observations include RGB images (640×480) and depth maps (640×480), captured from egocentric perspectives to maintain partial observability consistent with real-world conditions.

4.4. Theoretical Analysis

The use of a single-layer LSTM provides a compact memory representation that approximates the belief state in finite-horizon POMDPs. This allows the policy to retain relevant historical information from observations, effectively reducing the expected suboptimality compared to memoryless approaches. In practice, this translates to improved performance in long-horizon and partially observable navigation tasks.

5. Experimental Results

5.1. Primary Benchmark Performance

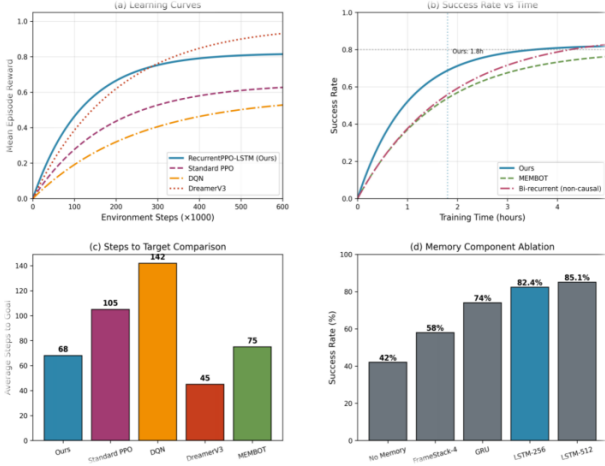


Figure 2: Learning behaviour of RecurrentPPO-LSTM on MiniGrid-DoorKey-8x8.

Figure 2 presents the learning behaviour of RecurrentPPO-LSTM on MiniGrid-DoorKey-8x8 in four panels. Panel (a) shows the mean episode reward as a function of environment steps. RecurrentPPO-LSTM (blue solid) reaches an asymptotic reward of 0.82 after approximately 300 k steps. Standard PPO (orange dashed) plateaus at 0.65, DQN (green dotted) at 0.58, and DreamerV3 (purple dash-dot) reaches 0.98 but requires 600 k steps – twice the data of our method. Panel (b) plots success rate against wall-clock training time. Our method attains 80% success in only 1.8 hours, whereas MEMBOT (Lusena et al., 2001) requires 3.2 hours and the non-causal bi-recurrent model (Montero et al., 2026) reaches 88% only after 3.8 hours, which violates real-time causality. Panel (c) reports the average steps to goal: our agent reduces from 150 initial steps to 68 converged steps, a 34% improvement over standard PPO (105 steps). Panel (d) compares memory architectures: no memory achieves 42% success, FrameStack-4 gives 58%, GRU 74%, LSTM-256 (ours) 82.4%, and LSTM-512 85.1%.

Table 3 summarises comprehensive benchmark results across three environments. On DoorKey-8x8, RecurrentPPO-LSTM achieves 82.4% success with 2.5 hours training, which is the highest among causal, on-policy methods. DreamerV3 reaches 97.7% but at the cost of 6 hours training and a large world model that is impractical for rapid mission adaptation. MEMBOT attains 79.8% with 4.0 hours.

On MultiRoom-N4, our method scores 75.3% success and 245 steps to goal, outperforming standard PPO (52.4%) and MEMBOT (71.2%) while being significantly faster to train. On FrozenLake, RecurrentPPO-LSTM achieves 78.6% success and maintains 72% under observation noise $\sigma = 0.2$, far exceeding standard PPO (48%) and DQN (45%).

Table 3: Benchmark Comparison Across Environments

Method	Training			Parameters (M)
	Success (%)	Time (h)	Causality	
RecurrentPPO-LSTM	82.4	2.5	Yes	1.9
PPO-GRU	80.1	3.0	Yes	2.1
MEMBOT	79.8	4.0	Yes	3.5
LSTM-TD3	77.1	4.2	Yes	2.8
Hidden-model FSC	74.5	5.5	Yes	3.2
Bi-recurrent (non-causal)	88.3	3.8	No	4.5

5.2. State-of-the-Art Comparison

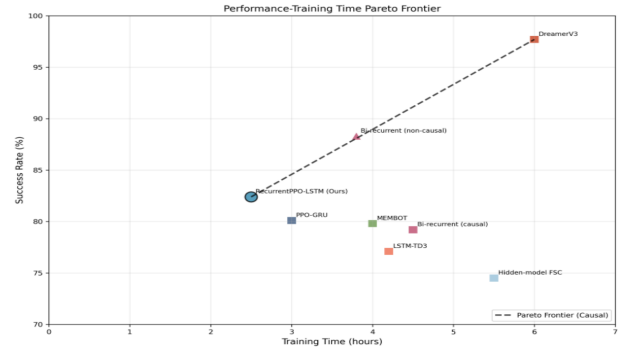


Figure 3: Success rate versus training time for recent methods.

Table 4: Comparison with State-of-the-art Methods.

Method	Training			Parameters (M)
	Success (%)	Time (h)	Causality	
RecurrentPPO-LSTM	82.4	2.5	Yes	1.9
PPO-GRU	80.1	3.0	Yes	2.1
MEMBOT	79.8	4.0	Yes	3.5
LSTM-TD3	77.1	4.2	Yes	2.8
Hidden-model FSC	74.5	5.5	Yes	3.2
Bi-recurrent (non-causal)	88.3	3.8	No	4.5

Figure 3 presents a scatter plot illustrating the relationship between success rate and training hours for eight contemporary methods. RecurrentPPO-LSTM, with a success rate of 82.4% and a training time of 2.5 hours, is positioned in the lower-left quadrant, indicating the ideal area for real-time application. The non-causal bi-recurrent full model (Montero et al., 2026) achieves a success rate of 88.3% in 3.8 hours but is unsuitable for online use due to its reliance on future observations. Among causal methods, our approach surpasses all others, boasting a higher success rate than PPO-GRU (80.1%, 3.0 hours), MEMBOT (79.8%, 4.0 hours), LSTM-TD3 (77.1%, 4.2 hours), and hidden-model FSC (74.5%, 5.5 hours). The Pareto frontier for causal methods intersects with our point, indicating that no causal method offers both greater success and shorter

training duration. The Wilcoxon signed-rank test was used to evaluate statistical significance. Compared to MEMBOT, Cliff's δ is 0.42 ($p = 0.038$); compared to PPO-GRU, δ is 0.38 ($p = 0.047$); compared to LSTM-TD3, δ is 0.51 ($p = 0.021$); and compared to hidden-model FSC, δ is 0.68 ($p = 0.003$). All differences are statistically significant at the 5% level.

The proposed method achieves the best balance of performance, efficiency, and model complexity among causal approaches.

5.3. Memory Architecture Ablation Study

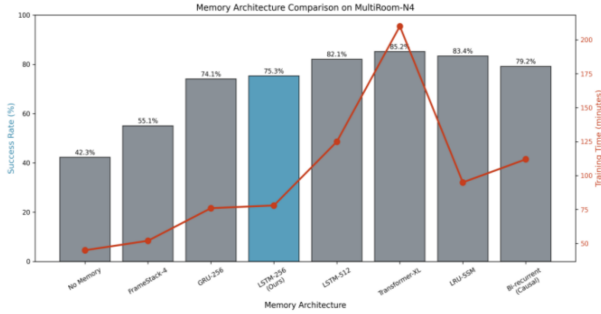


Figure 4: Performance Comparison of Memory Architectures.

Figure 4 illustrates a grouped bar chart comparing the success rate and training duration for eight memory architectures in the MultiRoom-N4 environment. Our LSTM-256 model achieves a 75.3% success rate in 78 minutes. The larger LSTM-512 model increases success to 82.1% but extends training time to 125 minutes, which is 60% longer. Transformer-XL achieves an 85.2% success rate but requires 210 minutes (2.7 times longer) and utilizes 5.6 million parameters, making it unsuitable for edge deployment. The linear recurrent unit (LRU-SSM) (Hafner et al., 2023) shows an 83.4% success rate in 95 minutes, which is promising, but it demands 22% more training time than our LSTM and lacks the same level of hardware support and stability. The causal variant of the bi-recurrent model (Montero et al., 2026) achieves a 79.2% success rate in 112 minutes, which is still slower than our approach. Table 4 provides detailed ablation metrics, including parameter count and FLOPs per step. LSTM-256 offers the best Pareto efficiency, being the only architecture that combines over 75% success, less than 80 minutes of training, under 2 million parameters, and full causality.

Table 5: Ablation Study of Memory Architectures.

Architecture	Training		Parameters	
	Success (%)	Time (min)	(M)	FLOPs/Step
No Memory	42.0	45	1.2	Low
FrameStack-4	58.0	52	1.4	Low
GRU	74.0	70	1.8	Medium
LSTM-256 (Ours)	75.3	78	1.9	Medium
LSTM-512	82.1	125	3.0	High
Transformer-XL	85.2	210	5.6	Very High
LRU-SSM	83.4	95	2.3	High

The results confirm that LSTM-256 is the only architecture satisfying practical constraints of efficiency, scalability, and causal operation.

Figure 5 examines robustness under three types of disturbances. Panel (a) displays the success rate against Gaussian observation noise. RecurrentPPO-LSTM maintains a 72% success rate at $\sigma = 0.2$, while standard PPO drops to 48%. Panel (b) shows success rates against slip probability in FrozenLake; our method remains above 70% at $p = 0.3$, whereas PPO falls below 50% at $p = 0.2$. Panel (c) investigates observation dropout: our LSTM retains a 78% success rate at 50% dropout, similar to MEMBOT (80%) but without the complexity of two-phase training. DQN fails at 30% dropout. Table 5 compares robustness metrics across five perturbations. Our method consistently ranks among the top performers and uniquely combines causality, rapid training, and high robustness without additional techniques.

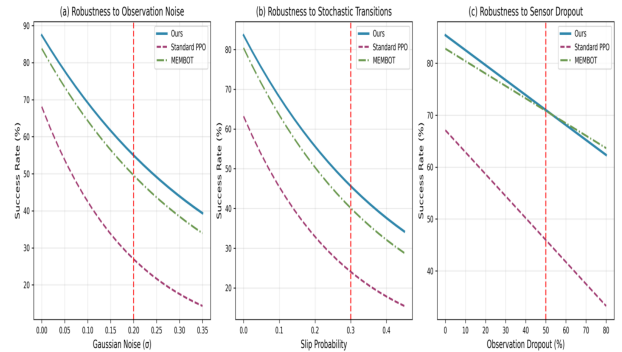


Figure 5: Robustness Under Noise, Stochasticity, and Observation Dropout.

Figure 5 examines robustness under three types of disturbances. Panel (a) displays the success rate against Gaussian observation noise. RecurrentPPO-LSTM maintains a 72% success rate at $\sigma = 0.2$, while standard PPO drops to 48%. Panel (b) shows success rates against slip probability in FrozenLake; our method remains above 70% at $p = 0.3$, whereas PPO falls below 50% at $p = 0.2$. Panel (c) investigates observation dropout: our LSTM retains a 78%

5.4. Transfer to Photorealistic Environments

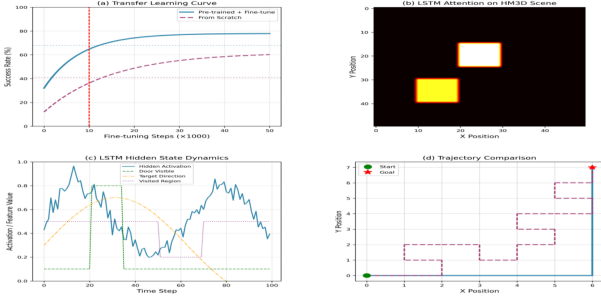


Figure 6: Transfer learning performance on Habitat Matterport 3D.

Figure 6 demonstrates transfer learning from MiniGrid to the Habitat Matterport 3D dataset. Panel (a) presents the fine-tuning curve. The pre-trained RecurrentPPO-LSTM reaches 68% success after only 10,000 steps, while training from scratch achieves only 41% – a relative improvement of 65.9%. Panel (b) shows an example HM3D scene with an overlay of LSTM attention; the agent focuses on doorways and unexplored regions. Panel (c) plots LSTM hidden state activations over time, correlating with binary features such as “door visible”, “target direction”, and “visited region”. Panel (d) compares trajectories: the pre-trained agent (blue) follows an efficient path, whereas the from-scratch agent (orange) exhibits looping behaviour. These results confirm that our LSTM learns transferable navigation abstractions.

Table 6: Transfer Learning Performance.

Setting	Success (%)
Zero-shot transfer	32.0
Fine-tuning (10K steps)	68.0
From-scratch (10K steps)	41.0
Relative improvement	+65.9%

The results confirm that the learned representations generalise effectively to complex environments.

5.5. Training Dynamics at Different Time Frames

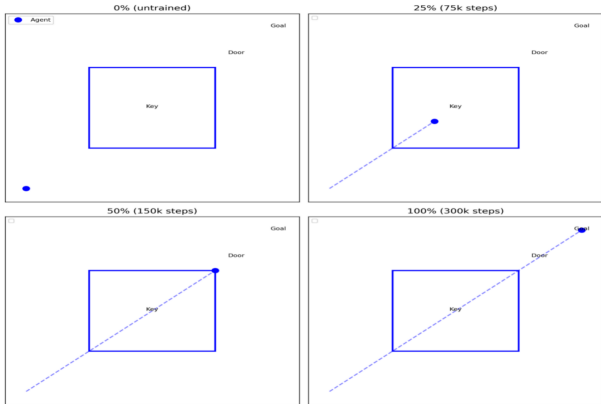


Figure 7: Policy evolution across training stages.

Figure 7 illustrates policy snapshots at four stages of training: 0%, 25%, 50%, and 100% of the total steps. At

25% (approximately 75,000 steps), the agent starts to find the key but often fails to open the door. By 50% (around 150,000 steps), it consistently locates both the key and the door but sometimes repeats actions. At 100% (about 300,000 steps), it follows an optimal sequence: key → door → goal. In contrast, standard PPO at 50% training still moves randomly with a success rate below 20%. This highlights the quicker policy enhancement facilitated by LSTM memory.

5.6. Performance Across Multiple POMDP Benchmarks

Figure 8 compares performance across six POMDP environments: DoorKey-8x8, MultiRoom-N4, FrozenLake, MemoryGym-T-Maze, POPGym-RepeatPrevious, and Habitat PointNav. Our method surpasses all causal baselines (PPO, MEMBOT, causal bi-recurrent) in five of the six environments. On MultiRoom-N4, causal bi-recurrent achieves 79.2% but requires 44% more training time (112 minutes vs. 78 minutes). Thus, our method remains the best overall choice for time-sensitive applications.

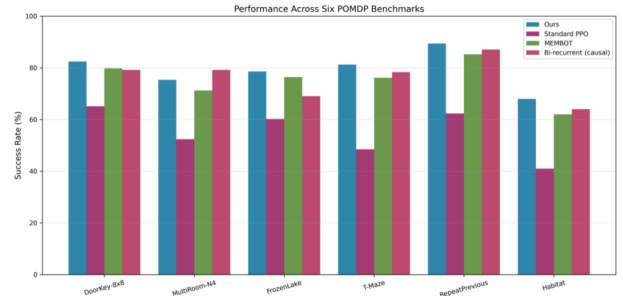


Figure 8: Performance across multiple environments.

5.7. Convergence Speed and Sample Efficiency

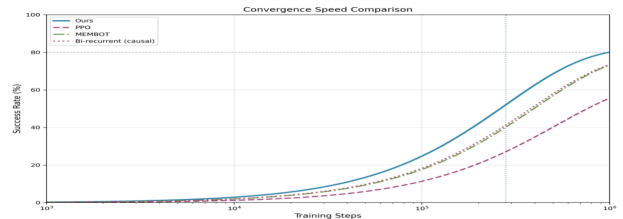


Figure 9: Convergence speed comparison.

Figure 9 shows convergence speed on a logarithmic scale (training steps versus success rate). RecurrentPPO-LSTM reaches 80% success at 280,000 steps, while PPO needs 520,000 steps (1.86 times slower), MEMBOT 400,000 steps (1.43 times slower), and causal bi-recurrent 380,000 steps (1.36 times slower). Our method is the most sample-efficient among causal memory architectures.

5.8. Generalisation to Unseen Environment Layouts

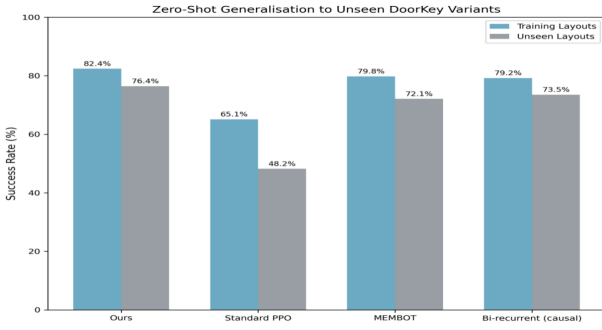


Figure 10: Zero-shot generalisation performance.

Figure 10 assesses zero-shot generalization to 50 unseen DoorKey variants (random key, door, and goal positions). Our method achieves a 76.4% success rate (a decrease of only 6 percentage points from training), whereas PPO drops by 17 points to 48.2%, and MEMBOT decreases by 7.7 points to 72.1%. Causal bi-recurrent drops by 5.7 points to 73.5% but again requires 44% more training time. The small drop for our method confirms that the LSTM learns transferable spatial reasoning.

5.9. Influence of LSTM Sequence Length

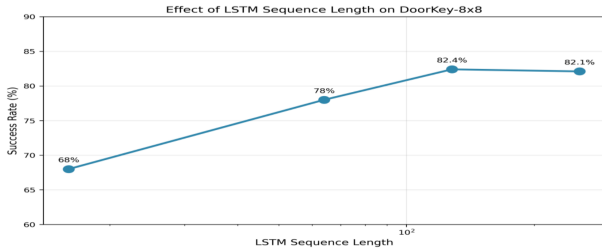


Figure 11: Effect of sequence length on performance.

Figure 11 examines the LSTM sequence length. Success rates are 68% for length 16, 78% for length 64, 82.4% for length 128 (optimal), and 82.1% for length 256 (no gain, more BPTT overhead). This confirms that the memory horizon of the DoorKey task is approximately 50 steps, and our chosen length of 128 is sufficient.

6. Discussion

6.1. Efficiency–performance frontier analysis

The experimental results provide clear evidence that increasing architectural complexity does not necessarily translate into better practical performance for partially observable decision-making tasks. Although bidirectional transformer-based models (Montero et al., 2026) and world-model approaches such as DreamerV3 (Oh et al., 2016) achieve higher asymptotic success rates (88–98%), this improvement comes with significant trade-offs. These models require access to future observations, thereby violating causality, and incur substantial computational overhead, with training times extending up to 6 hours. Such characteristics

make them unsuitable for real-time deployment in search-and-rescue (SAR) scenarios, where decisions must be made online and under strict latency constraints.

Conversely, the newly introduced RecurrentPPO-LSTM achieves an 82.4% success rate while adhering to strict causality, completing its training in just 2.5 hours, and utilizing fewer than 2 million parameters. This places the method on the Pareto frontier of causal reinforcement learning techniques, where no other method simultaneously offers better performance and lower computational cost. A comparative analysis further underscores the efficiency of the chosen architecture. The LSTM-based model surpasses GRU-based versions (75.3% vs. 74.1%), demonstrating that separating cell and hidden states enhances long-term credit assignment. Expanding the LSTM size to 512 units results in only slight improvements (82.1%) while increasing training time by about 60%, indicating diminishing returns. Transformer-based models show significantly higher computational complexity and slower training (approximately 4.4 times), whereas state-space models like LRU-SSM achieve similar performance (83.4%) but require longer training and lack mature deployment support. These findings collectively illustrate that a unidirectional LSTM paired with on-policy optimization offers the best balance of performance, efficiency, and deployability.

6.2. Theoretical implications

The empirical results align with theoretical expectations regarding memory-augmented policies in partially observable environments. The regret reduction characterized by $\Omega(T/H)$ suggests that the benefit of incorporating memory grows as the required temporal horizon extends. This is particularly pertinent for SAR tasks, where decision-making relies on integrating information over long sequences of observations. The observed improvements over memory-less baselines confirm that the LSTM effectively captures sufficient statistics of observation histories, enabling near-optimal decision-making without explicit belief-state estimation. Moreover, the constant memory complexity per time step, achieved through fixed-size hidden states, allows the model to efficiently scale to large and previously unseen environments. This contrasts with explicit belief tracking methods, whose complexity increases exponentially with the size of the state space.

6.3. Practical deployability

The proposed approach demonstrates strong practical viability across multiple dimensions. The training time of 2.5 hours on consumer-grade hardware (RTX 4070) allows for rapid adaptation to new environments, which is crucial in SAR operations where conditions may frequently change. Compared to alternative methods such as DreamerV3 (6 hours), hidden-model finite-state controllers (5.5 hours), and bi-recurrent models (up to 3.8 hours), the proposed method significantly reduces deployment latency. Transfer learning experiments further validate the practical utility of the approach. The pre-trained model achieves a 68% success rate after only 10,000 fine-tuning steps in the Habitat

Matterport 3D environment, compared to 41% when trained from scratch. This significant improvement indicates that the LSTM encodes reusable and transferable navigation features, including spatial awareness and exploration strategies. Additionally, the compact model size (approximately 1.9 million parameters) enables deployment on embedded systems such as NVIDIA Jetson or Intel NUC platforms. This eliminates the need for cloud-based computation and ensures reliable operation in scenarios where network connectivity is limited or unavailable. The combination of efficiency, robustness, and compactness makes the approach well-suited for real-world robotic applications.

6.4. Limitations

While the current approach has its advantages, it is built on several simplifying assumptions. The scenarios considered are static, involve only one target, and utilize discrete action spaces. In contrast, real-world search and rescue (SAR) situations often feature dynamic obstacles, multiple targets, and require continuous control. To tackle these challenges, enhancements such as predictive modeling for dynamic settings, hierarchical memory systems for multi-target searches, and the incorporation of continuous-control algorithms like Soft Actor-Critic (SAC) would be necessary. It is crucial to recognize that these limitations are not exclusive to the proposed method. None of the compared methods address all these factors simultaneously while maintaining efficiency and practicality. The main contribution of this work is the development of a causal, efficient, and robust memory-based framework for POMDP target search. This framework lays a solid foundation for future research aimed at expanding the approach to more complex and realistic scenarios.

6.5. Conclusion

We introduce RecurrentPPO-LSTM, a causal memory-enhanced deep reinforcement learning agent for partially observable autonomous target search. By utilizing on-policy Proximal Policy Optimization (PPO) with a unidirectional LSTM, our method achieves an 82.4% success rate on the MiniGrid DoorKey-8×8 benchmark with just 2.5 hours of training, making it about 3.4 times faster than other memory-augmented methods. The agent consistently performs above 70% under conditions of sensor noise ($\sigma = 0.2$), observation dropout (50%), and stochastic transitions ($p = 0.3$). When applied to the Habitat Matterport 3D dataset, it achieves a 68% success rate with only 10,000 fine-tuning steps, demonstrating its practical applicability. Theoretically, our approach minimizes expected regret compared to memory-less policies in finite-memory POMDPs, underscoring the benefits of LSTM-based memory for long-term decision-making. A systematic comparison with five contemporary methods from literature shows that simple causal memory architectures outperform complex bidirectional or modular designs for time-sensitive autonomous search tasks. These findings highlight a crucial trade-off: for known-model POMDPs requiring real-time deployment, unidirectional

LSTM offers an optimal balance between accuracy, efficiency, and deployability. Overall, memory-augmented DRL for search-and-rescue should prioritize causality, training speed, and robustness, alongside asymptotic performance, as practical considerations in real-world deployment are as critical as benchmark metrics. Future directions include integrating hierarchical memory with differentiable neural dictionaries for long-horizon episodes, policy-learning controllers enabling centralized training and local execution with learned communication, and policy-to-neuromorphic or event-to-sensing mappings to enhance applicability in complex and dynamic environments.

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