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Meta-Learned Adaptive Memory Filtering for Robust Multi-Agent Collaboration

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Abstract

Static defense rules may fail under evolving poisoning strategies. This work introduces a meta-learning framework that adapts memory filtering parameters based on historical contamination patterns. A meta-optimizer updates filtering thresholds using second-order gradient estimation across poisoning episodes. The framework was evaluated on cooperative resource management simulations with 50 agents across 200 poisoning scenarios. Adaptive filtering reduced cumulative task performance loss by 44.8% compared with fixed-threshold filtering. Convergence speed improved by 19.5% under dynamic attack conditions. Meta-adaptive filtering enhances resilience against non-stationary memory poisoning strategies.

Keywords

Meta-learning; multi-agent systems; adaptive filtering; memory poisoning; collaborative robustness; dynamic defense

1.Introduction

Multi-agent systems (MAS) are widely used in cooperative resource management, distributed control, and autonomous coordination, where multiple agents must exchange information continuously to maintain effective group behavior. In these settings, shared memory is an important support mechanism because it stores local observations, coordination records, and intermediate task states that may be reused in later decision rounds. The reliability of this memory has a direct influence on collective performance, especially in tasks that depend on repeated interaction, delayed feedback, and long-horizon coordination. Recent surveys indicate that multi-agent reinforcement learning is moving toward larger-scale, more adaptive, and more open environments, which increases both system flexibility and exposure to instability and attack [1,2]. At the same time, recent studies on memory contamination in collaborative environments suggest that once poisoned content enters the shared state, it may propagate through repeated synchronization, affect subsequent retrieval and coordination, and remain active over multiple interaction rounds [3]. This risk is especially important in MAS because contaminated records are not merely read once; they can be reused, reweighted, and redistributed across agents, making local corruption a potential source of broader system degradation. In practice, memory corruption is rarely caused by a single fixed threat model. It may arise from evolving poisoning strategies that exploit repeated interaction, gradual contamination, or the accumulation of misleading records over time. Under such conditions, a defense rule that performs well at one stage may become ineffective at another, particularly when the attacker changes behavior in response to system feedback. Research on adversarial learning has repeatedly shown that adaptive attacks remain

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difficult to handle in sequential decision systems because the interaction between attacker and defender unfolds over time rather than in one isolated step. In reinforcement learning, studies on reward poisoning have shown that defense cannot rely solely on static screening rules, since the effect of poisoned feedback often depends on temporal context and policy evolution [4,5]. Related studies also suggest that strong protection is difficult to maintain when attack strategies change during interaction or when the defender is optimized for only a narrow threat pattern [6,7]. Within multi-agent reinforcement learning, recent reviews further report that coordinated policies can be highly sensitive to targeted disturbances in shared information channels [8]. Work on non-stationary multi-agent learning also shows that even in the absence of an attacker, policy stabilization is already difficult because the interaction process changes continuously during training and deployment [9,10]. Taken together, these findings suggest that poisoning defense in collaborative systems should not depend only on fixed thresholds, manually tuned rules, or one-time calibration. Meta-learning has received growing attention as a promising way to improve adaptation under task variation, uncertainty, and changing operating conditions. Recent studies show that meta-learning can help reinforcement learning systems adapt more efficiently to unseen environments, dynamic role assignments, and task distributions that differ from training conditions [11]. In multi-agent settings, meta-learning has also been used to improve adaptive cooperation, role-aware coordination, and hierarchical decision-making under changing interaction structures [12]. Related work on adaptive hypernetworks, task-conditioned parameter generation, and adaptive exploration has further shown that flexible parameter updates can improve robustness when the environment or interaction pattern changes over time. Although these studies were not originally developed for memory poisoning defense, they provide an important conceptual basis: when the environment is non-stationary, effective decision rules should be updated from experience rather than kept fixed throughout the whole process. This idea is highly relevant to shared-memory protection, where the characteristics of harmful records may shift across attack episodes and where a rigid filtering rule may either miss malicious updates or remove too much useful information. A related body of work has focused more directly on poisoning resistance and memory protection. In federated learning and distributed training, recent studies show that meta-learning can improve robustness against mixed and adaptive poisoning attacks by learning how to respond across multiple attack episodes instead of optimizing for a single threat model [13]. In memory-based agent systems, recent work has argued that memory should not be treated as a passive storage unit, but as an active component that requires monitoring, checking, and repair when harmful content accumulates [14]. Broader security reviews also indicate that adaptive attackers can bypass many fixed defensive rules by changing trigger patterns, attack timing, or contamination intensity over time. These findings are important, but most existing defenses still focus on LLM memory stores, reward channels, model aggregation, or general security layers. Comparatively less attention has been given to adaptive filtering of shared memory in collaborative MAS, where contamination may spread through repeated coordination and where the most suitable filtering rule may vary across poisoning stages. Several limitations remain in the current literature. Many defense methods still rely on fixed thresholds, static trust scores, or hand-crafted filtering rules, which restricts their usefulness when attack behavior changes during long interaction sequences [15]. A large portion of existing evaluations is also conducted under relatively narrow attack settings, simplified benchmarks, or single-stage poisoning patterns, making it difficult to judge whether a method can remain effective under longer and more varied attack processes [16]. At the same time, research on multi-agent adaptation has

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mainly concentrated on policy learning, role transfer, exploration, or coordination efficiency, while adaptive filtering and repair of shared memory under evolving contamination have received much less attention [17]. This omission is nontrivial because memory poisoning is often cumulative rather than instantaneous. Early contamination may alter later retrieval, bias coordination records, and gradually change decision quality across multiple agents. In such cases, the defense problem is not limited to identifying a suspicious current input; it also requires the system to respond to contamination history, update its screening behavior, and maintain useful information flow without excessive filtering. From a system perspective, this gap has practical significance. Collaborative MAS deployed in resource management and distributed control must often operate for long periods under uncertain and partially observed conditions. These systems depend on memory not only to preserve past information, but also to reduce repeated computation, support coordinated planning, and stabilize cooperation among agents with incomplete local views. Once this memory channel becomes contaminated, the resulting error may not remain local. It can influence future filtering decisions, distort the shared basis for coordination, and weaken the reliability of the collective policy. A desirable defense mechanism should therefore satisfy several requirements simultaneously: it should adapt to evolving contamination patterns, reduce the cumulative influence of poisoned memory, preserve beneficial shared information, and remain computationally feasible for repeated deployment in distributed settings. Existing approaches rarely meet all of these conditions at the same time. The present study proposes a meta-learned adaptive memory filtering framework for robust multi-agent collaboration. The central idea is that filtering parameters should be updated according to historical contamination patterns rather than remain fixed across all poisoning episodes. In the proposed framework, a meta-optimizer adjusts memory filtering thresholds through second-order gradient estimation over repeated attack scenarios, enabling the filtering mechanism to respond to changing poisoning behavior and contamination intensity. This design reframes memory defense as an adaptive learning problem rather than a static screening procedure, and it places the adaptive update mechanism directly at the memory filtering stage, where poisoned content begins to affect later collaboration. The study evaluates whether such a meta-adaptive strategy can reduce cumulative task loss, improve convergence stability, and preserve coordination quality under dynamic poisoning conditions in cooperative multi-agent resource management. By introducing meta-learning into shared-memory defense, this work extends the scope of poisoning mitigation from fixed-rule detection to experience-driven adaptive protection, and provides a more practical basis for improving the long-term reliability of collaborative multi-agent systems in adversarial environments.

2.Materials and Methods

2.1. Sample and Simulation Setting

The study was carried out in a cooperative resource management simulation built for multi-agent collaboration with shared memory exchange. The system included 50 agents. Each agent kept a local memory buffer for recent observations, coordination records, and task-related state information. The simulation represented a dynamic collaborative setting in which agents repeatedly updated shared memory under changing attack conditions. A total of 200 poisoning scenarios were generated to cover different contamination patterns, attack levels, and time-varying poisoning behavior. All experiments were performed under the same task schedule, communication interval, and resource allocation rules. This kept the test conditions stable across runs and allowed the

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effect of adaptive filtering to be examined under comparable non-stationary poisoning settings.

2.2. Experimental Design and Control Setting

A comparative design was used to evaluate the proposed meta-adaptive filtering method against a fixed-threshold baseline. In the control setting, memory filtering used a constant threshold selected before training and kept unchanged across all poisoning episodes. In the experimental setting, filtering thresholds were updated by a meta-optimizer based on historical contamination patterns observed over repeated attack episodes. Both settings were tested under the same 200 poisoning scenarios and the same cooperative task environment. This design allowed a direct comparison between a static defense rule and an adaptive filtering strategy under changing attack behavior. The comparison was necessary because fixed-threshold filtering is simple and widely used, but its performance may decline when poisoning patterns change over time. In contrast, the proposed method aimed to adjust the filtering rule to the current attack condition while keeping useful memory content for later collaboration.

2.3. Measurement Method and Quality Control

During each simulation episode, memory updates generated by the agents were collected and checked before being passed to the shared coordination layer. In the control setting, the same filtering threshold was applied to all episodes. In the adaptive setting, the threshold was updated through a meta-learning process after each poisoning episode. Cumulative task performance loss and convergence speed were used as the main evaluation measures. Task performance loss was defined as the reduction in cooperative task reward caused by contaminated memory, while convergence speed was measured by the number of training iterations required for the system to return to stable performance under attack. To keep the results reliable, all agents used the same initialization rule, memory size, and task objective. The poisoning schedule, task demand profile, and episode length were also kept the same across repeated runs. Each experiment was repeated several times, and the final results were reported as mean values. Runtime logs were checked after each run to confirm that performance changes were caused by poisoning and filter response rather than by unrelated simulation errors.

2.4. Data Processing and Model Formulation

The raw records from each poisoning episode were first grouped by defense setting and then summarized across repeated runs. Let θ_t denote the filtering threshold at episode t. In the fixed-threshold baseline, θ_t remained unchanged for all episodes. In the proposed framework, the threshold was updated through meta-learning as

$$\theta_{t+1}=\theta_t-\alpha\nabla_\theta L_{meta}(\theta_t),$$

where α is the meta-learning rate and L_{meta} is the meta-objective defined over poisoning episodes. Cumulative task performance loss was calculated as

$$L_c=\sum_{t=1}^{T}(R_t^*-R_t),$$

where R_t^* is the reference reward under clean memory and R_t is the observed reward under poisoning at episode t. Improvement in defense performance was measured by

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comparing the cumulative loss and convergence speed of the adaptive method with those of the fixed-threshold baseline. All results were summarized as mean values over repeated poisoning scenarios.

2.5. Evaluation Criteria and Statistical Analysis

The proposed method was evaluated from two aspects: resistance to poisoning and adaptation efficiency. Resistance to poisoning was measured by the reduction in cumulative task performance loss under dynamic attacks. Adaptation efficiency was measured by the speed at which the system reached stable performance across poisoning episodes. These two indicators were examined together because a useful filtering method should not only reduce the damage caused by poisoned memory, but also adapt quickly to changing attack patterns. To reduce random variation, repeated trials were conducted under each setting and mean values were used for comparison. Relative improvement was reported as the percentage decrease in cumulative task loss and the percentage increase in convergence speed compared with the fixed-threshold baseline. This evaluation made it possible to judge whether the proposed meta-adaptive filtering framework provided more stable protection than a static filtering rule under non-stationary poisoning conditions.

3. Results and Discussion

3.1. Overall effect of adaptive filtering under dynamic poisoning

The proposed method performed better than the fixed-threshold baseline across the 200 poisoning scenarios. Adaptive filtering reduced cumulative task performance loss by 44.8%. This result shows that the filter adjusted to changing contamination patterns more effectively than a static rule. This point is important in cooperative resource management, where shared memory directly affects later allocation and coordination decisions. Recent survey work shows that multi-agent reinforcement learning is increasingly used in dynamic and decentralized resource allocation settings, where changing system conditions are part of the problem itself [18,19]. In such environments, a defense rule that stays fixed is less likely to remain effective over time. The present result supports this view and shows that memory filtering should adapt to attack history rather than depend only on a threshold chosen in advance (Fig. 1).

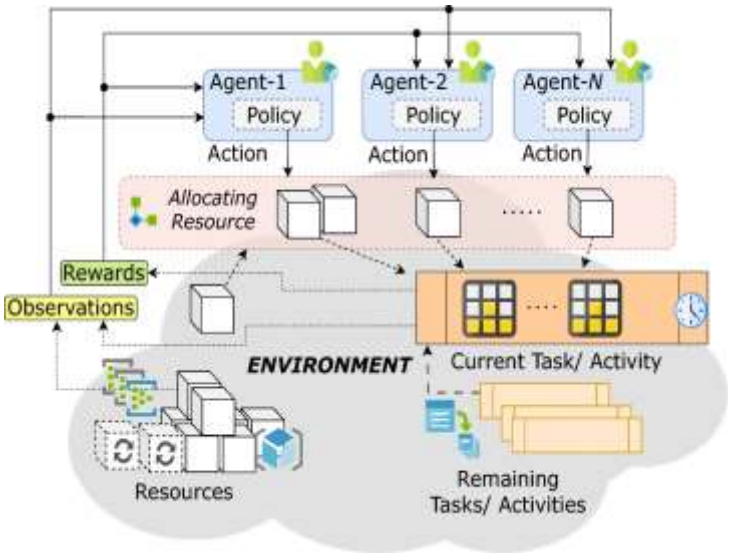

Figure 1:Cumulative task loss under adaptive and fixed-threshold memory filtering.

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3.2. Improvement in convergence under non-stationary attacks

The adaptive framework also improved convergence speed by 19.5% under changing attack conditions. This result suggests that the benefit of the method was not limited to reducing immediate task loss. It also helped the system return more quickly to stable cooperative behavior after poisoning episodes. One possible reason is that the meta-optimizer updated the filtering threshold from earlier contamination patterns, which reduced repeated mismatch between the defense rule and the current attack form. Recent work on meta-learning for security tasks shows that learning from multiple attack environments can improve adaptation to new threat conditions [20,21]. Although that literature does not focus on multi-agent memory, the same idea applies here: when the threat changes over time, a defense mechanism that learns how to adjust can recover faster than one that remains unchanged (Fig. 2).

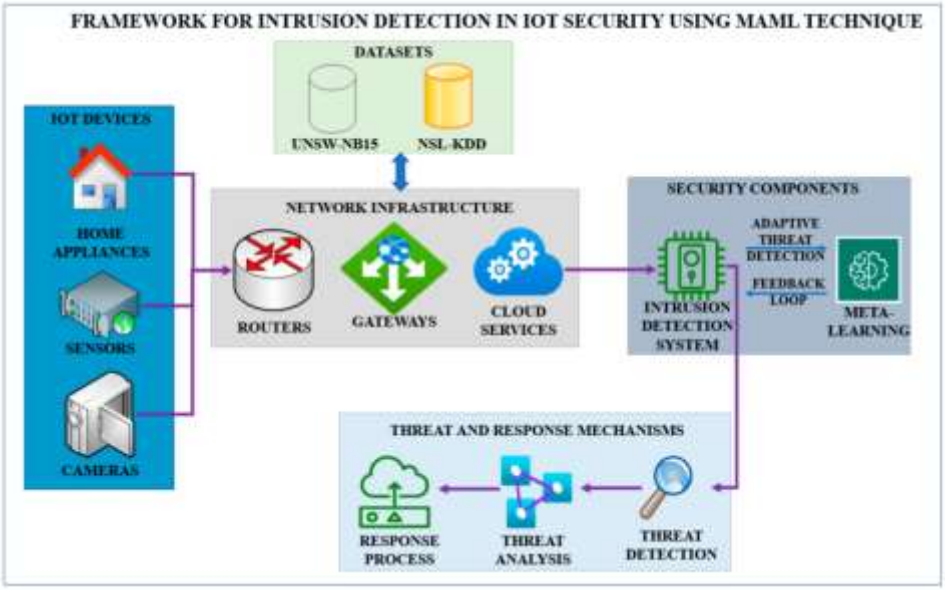

Figure 2:Convergence speed of the adaptive filtering method under dynamic poisoning.

3.3. Comparison with existing studies

Compared with earlier studies, the main strength of the present method is that adaptation is introduced at the memory filtering stage rather than only at the policy or model-update stage. Much of the existing work on robust multi-agent learning focuses on communication robustness, adversarial training, or certified policy behavior. Other studies in meta-learning mainly aim at fast task adaptation, few-shot transfer, or adaptive exploration. These directions are important, but they do not directly address the problem considered here, namely that shared memory can be gradually corrupted by changing poisoning strategies and therefore needs a defense rule that changes with the attack process. The present findings extend earlier robust multi-agent work by showing that adaptation at the filtering layer can reduce both accumulated task loss and recovery time in collaborative settings [22,23].

3.4. Practical meaning and remaining limits

The results suggest that meta-adaptive filtering is a practical way to strengthen memory robustness in collaborative multi-agent systems. The method gave better protection under non-stationary poisoning while keeping the learning process responsive to new attack conditions. This feature is especially useful in open or long-running systems,

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where attackers may change strategy after observing earlier defenses. At the same time, the present study has several limits. The experiments were carried out in a 50-agent simulation with 200 poisoning scenarios, and the adaptive rule was learned from second-order gradient updates under a controlled resource management setting. Real systems may involve larger agent populations, more complex memory structures, and more abrupt shifts in attack behavior. In addition, the current comparison was limited to a fixed-threshold baseline. Future work should therefore compare the proposed method with stronger adaptive baselines and test its performance in broader multi-agent applications.

4.Conclusion

This study proposed a meta-learned adaptive memory filtering method for robust multi-agent collaboration under dynamic poisoning attacks. The results showed that the method reduced cumulative task loss by 44.8% compared with fixed-threshold filtering and improved convergence speed by 19.5% under changing attack conditions. These results suggest that fixed filtering rules are often not enough when poisoning behavior changes over time. The main contribution of this work is that it treats memory defense as an adaptive learning task and updates filtering thresholds from past contamination patterns instead of keeping them unchanged across all attack episodes. This design gives the method clear scientific value because it links memory protection with meta-learning and shows that attack history can improve later defense decisions. The method also has practical value for cooperative resource management, distributed control, and other multi-agent systems in which shared memory directly affects later coordination quality. At the same time, the present study was conducted in a controlled simulation with 50 agents and 200 poisoning scenarios, and the comparison was limited to a fixed-threshold baseline. Further work is still needed under larger system scales, more complex memory structures, and stronger adaptive attack settings. Future studies should also compare the proposed method with other adaptive defense strategies and examine its performance in real multi-agent applications. Overall, the findings suggest that meta-adaptive memory filtering is a practical and effective way to improve robustness against non-stationary memory poisoning in collaborative systems.

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