Scaffolding Reflection in Reinforcement Learning Framework for Confinement Escape Problem

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Abstract—This paper formulates an application of reinforcement learning for an evader in a confinement escape problem. An evader’s objective is to attempt escaping a confinement region patrolled by multiple defenders, with minimum use of energy. Meanwhile, the defenders aim to reach and capture the evader without any communication between them. The problem formulation uses the actor-critic approach for the defender. In this paper, the novel Scaffolding Reflection in Reinforcement Learning (SR2L) framework is proposed, using a potential field method as a scaffold to assist the actor’s action-reflection. Through the user’s clearly articulated intent, the action-reflection enables the actor to learn by observing the probable actions and their values based on experience. Extensive Monte-Carlo simulations show the performance of a trained SR2L against the baseline approach. The SR2L framework achieves at least one order fewer episodes to learn the policy than the conventional RL framework.

I. INTRODUCTION

The recent developments in robotics and sensing technologies have created significant interest among researchers to deploy them for various territory surveillance problems. In particular, three problems have gained attention: territory protection, pursuit-evasion, and confinement escape. Territory protection requires multiple robots to tackle intruders cooperatively [1], [2]. In pursuit-evasion, an agent tries to capture the evader before it escapes a given region [3], [4]. A closely related problem called reach-and-avoid game is a class of planar multi-agent pursuit-evasion games. Unlike pursuit-evasion games, a team of evaders aims to avoid capture by a team of defenders while simultaneously attempting to reach a target location [5]–[7]. For confinement escape problems (CEP) [8], the evaders attempt to escape from confinement without being captured by the defenders. The formulation of CEP is an essential proxy for many robotic applications. In this problem, robots with varying degrees of cooperation and observation attempt to achieve designated objectives. It results in a high dimensional problem, thus increasing the complexity of obtaining an optimal CEP solution.

In literature, the first formulation for a typical confinement escape problem was given by [8]. It defines a circular confinement region and uses artificial forces between the agents to control the defenders and the evaders. [9], [10] provide further analysis of escape time with different initialization and the required winning conditions. These papers restrict the defenders’ motion to move along the circular boundary, thus providing a sub-optimal solution. Related work like [11] analytically formulates a control strategy for an evader to reach a given target location. It uses a subset of the evader’s state for a nonlinear state feedback control while removing any restrictions on the defenders. However, the proposed region-based control strategy performs well for a small number of pursuers only. The aforementioned works assume the evader has information regarding the entire region, thus causing dimensionality issues as the number of defenders increases. Also, analytical approaches use handcrafted features to get a solution. As all the features cannot be captured in a formulation, it may lead to a sub-optimal solution.

In this paper, an actor-critic reinforcement learning framework is proposed for an evader to escape the confinement against multiple defenders. A time-variant reward function is proposed for the evader to learn to extract essential features from the proposed time-variant state for an optimal solution. The evader uses partial observation by sensing the vicinity and prior knowledge about the static boundary to control its motion. Thus, avoiding the dimensionality issues and can work for any number of defenders. No restrictions are considered on a defender’s motion; they are free to move in any direction within the region. However, the evader to learn in such an uncertain and complex environment would require a significant amount of time. Therefore, a novel approach called scaffolding reflection in reinforcement learning (SR2L) is presented for faster and efficient learning. In the literature, the potential field method (PFM) has been extensively used in these problems [9], [10]. Therefore, in this paper, the PFM is used for scaffolding the evader’s learning process. The scaffold helps the evader reflect upon its action by observing the probable actions suggested by the PFM algorithm. Monte-Carlo simulations have been performed with many defenders to show the performance of a trained SR2L evader against PFM. The convergence study of SR2L training against conventional RL shows a significant reduction in time required for the evader to escape.

The remaining paper’s organization is as follows: Section II presents the mathematical formulation of the problem. Section III presents the decision-making framework and the proposed learning process. Section IV discusses the performance evaluation using Monte Carlo simulations and comparison with the conventional methods. Finally, the conclusions from the studies are summarised in section V.

II. CONFINEMENT ESCAPE PROBLEM DEFINITION

In this section, the Confinement Escape Problem (CEP) is formulated for the evader (E), with M defenders

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evader, whose range is $D_i$. The typical confined region with defenders and evader is shown in the Fig.\[1\] Let $Ω$ be the origin region where the evader $E$ is initialized and the defenders are distributed randomly in the entire closed region $R$ outside $Ω$. Note that the boundary $A$ of the region $R$ is closed and can be any shape. The objective of the evader $E$, is to escape from the closed confinement region without being captured by the defenders. The defenders search for the evader without any communication between them and try to capture or restrict the evader from escaping. The game is terminated, if the evader escapes the confinement region, or is captured. For example, in the Fig.\[1\] 8 defenders are initialized within the region $A$. Let, the position of the $i^{th}$ defender is represented as $P_i = [x_i, y_i]$. The defenders moves at different speed in search of evader, i.e, the speed of $i^{th}$ defender is $V_i^D$. The speed is restricted such that $V_{\text{min}}^D \leq V_i^D \leq V_{\text{max}}^D$. The heading direction of the $i^{th}$ defender $\psi_i^D$ is randomly initialized and the defender is free to change the heading direction without any constraint. Using the above definition, the motion of the $i^{th}$ defender is guided by the following equations.

$$\dot{x}_i^D = V_i^D \cos(\psi_i^D);$$

(1)

$$\dot{y}_i^D = V_i^D \sin(\psi_i^D);$$

(2)

where, $\psi_i^D$ represents the heading of the $i^{th}$ defender. The defenders are heterogeneous in nature, i.e., sensing range about the environment is different for different defenders. The defenders are equipped with Lidar sensors to detect the evader, whose range is $R_i$. It is assumed that the defenders maintain the speed and heading until it detects an evader or boundary of the confinement region. Upon reaching the boundary the defenders get deflected away from the boundary, thus changing its heading, while maintaining the speed. If the defender detects the evader, it starts chasing using a proportional-integral (PI) controller, with the maximum velocity limit being $V_{\text{max}}^D m/s$. In this game, $\delta d$ distance is considered to be the capture radius, i.e, if the distance between the evader and any defender is less than $\delta d$, it is considered as a successful capture.

For the evader $E$ to escape the confinement region, it uses a Lidar of range $R_E$ to sense its nearby environment and a GPS sensor for localization. It is assumed that the evader has information about the boundary and thus, can find the distance to the boundary from the current position. The position of $E$ with respect to the origin is $P_E = [x_E, y_E]$. Let the speed of the evader be $V_e$ and the heading be $\psi_e$. Note that the speed of evader is higher that the defenders, i.e., $V_e^D = V_{\text{max}}^D/V_{\text{max}}^D > 1$. The evader motion is guided by the following equations,

$$\dot{x}_E = V_E \cos(\psi_E)$$

(3)

$$\dot{y}_E = V_E \sin(\psi_E)$$

(4)

where, $V_E$ and $\psi_E$ represents the velocity and the heading of evader. The evader is initialized in the origin region $Ω$ with an initial velocity of $0 m/s$, along with a random heading angle $\psi_E$. Also, no defender is initialized in the region $Ω$.

It is assumed that, upon sensing, the evader can detect the defenders’ speed and heading direction. Also, the evader is equipped with a localization sensor to detect their position accurately. The evader aims to achieve a motion such that it avoids the defenders and reach the nearest boundary point as early as possible. Therefore the objective function for $E$ can be given as,

$$J = \min \left\{ \sum_{j=0}^{m} (R_E - d_j) + (R_B - d_b) \right\}$$

(5)

where $d_j$ is the distance from the $j^{th}$ defender among $m$ detected by the evader and $d_b$ is the distance of the evader from the nearest point of the boundary. Therefore, the mission is to escape the confinement region while minimizing the amount of energy consumed by the evader in the process.

III. SCAFFOLDING REFLECTION IN REINFORCEMENT LEARNING FOR CEP

In this section, first the actor-critic formulation of CEP in a reinforcement learning framework is given. Then the learning procedure followed by the description of the scaffolding reflection in reinforcement learning (SR2L) is presented.

A. Actor-critic formulation of CEP

In a reinforcement learning framework, the CEP is formulated as a Markov Decision Process (MDP). Here, the process is described by an experience tuple represented as $<s, a, r, s'>$. At any given time, $s$ represents the state of the evader in the environment. The evader interacts with the environment by choosing an action $a \in \mathcal{A}$ using a policy $\pi(a|s)$. The evader’s interaction with the environment leads to the next state $s'$ while gaining a reward $r$. The evader learns an optimal policy, $\pi^*(a|s)$, which gives the utility of the action space for its observed state. The goal of the evader is to learn a policy that maximizes the received discounted rewards. Here, $\gamma \in (0, 1]$ is the discount factor that determines how much the policy favors immediate reward over long-term rewards.

In this paper, an actor-critic deep reinforcement learning framework is used because of its ability to learn continuous action space. Conventionally, for the actor, a policy gradient
method is used to update actions so that actions with higher expected rewards have higher utility value for an observed state. Policy gradient techniques [12] estimates the gradient of expected utility values with given policy parameters $\theta$ using,

$$\nabla_\theta J(\pi_\theta) = \nabla_\theta \log(\pi_\theta(a|s_i))G(t); \quad (6)$$

where, $G(t)$ is the cumulative reward. Actor-critic methods [13] increase the stability by replacing cumulative rewards with a function approximation of the expected rewards. In this paper, the function approximation formulation (Q-value function) estimates expected discounted returns in a given state-action pair as,

$$Q_\psi(s_i, a_i) = E[\sum_{t'=t}^{\infty} r_{t'}(s_{t'}, a_{t'})] \quad (7)$$

Here, soft actor-critic [14] have been used to focused not only on maximizing long term rewards but also maximizing the entropy of the policy. The term entropy here refers to the the measure of unpredictability of a random variable. Maximum entropy RL learns a soft value function by modifying the policy gradient to incorporate an entropy term. Thus redefining $G(t)$ as:

$$G(t) = Q_\psi(s, a) - b(s) - a \log(\pi_\theta(a|s)) \quad (8)$$

where $b(s)$ is called the baseline for the Q-value function and $s$ is a function of state $s$. Actor critic learning is then achieved by minimizing the regression loss function given as:

$$L_Q(\psi) = E_{(s,a,r,s')}[(Q_\psi(s', a_i) - y) | (Q_\psi(s', a_i) - y)] \quad (9)$$

$$y = r(s, a) + \gamma E(Q_\psi(s', a') - a \log(\pi_\theta(a|s))) \quad (10)$$

Here, $Q_\psi$ refers to the target Q-value function and $y$ is the target value.

B. Actor-Critic framework for CEP

As mentioned earlier, the evader is equipped with a Lidar and a sensor for localization. To generate a point cloud, the Lidar is assumed to have a resolution of $N_s$. Every point in the point cloud, is associated with two values, i.e., the distance ($d_p^i \leq R_E^L$) and the angle from the evader frame of reference. Here, the point cloud data is represented as,

$$D_L[i] = K_s.(d_p[i]/R_E^L) \quad (11)$$

where, $i = 1, 2, ...., N_s$ and $K_s$ is a constant. For the evader to be able to escape the confinement, the evader is assumed to have information about the boundary of the confinement. Thus, with the help of localization sensor on board, the evader can calculate the distance ($d_n$) from the boundary points in all direction. To maintain the size of the data as that in case of Lidar, the resolution considered here is also $N_s$. This data is represented as,

$$D_B[i] = K_s.(1 - (d_n[i]/d_{n}^{max})) \quad (12)$$

where, $i = 1, 2, ...., N_s$ and $K_s$ is a constant. The same constant is used, to represent both types of data in the same scale. For the evader to escape the confinement as quickly as possible, the evader requires the information regarding the time elapsed in a given game. To embed this information to the state, a time factor $t_f$ is defined as,

$$t_f = (1 - (t/t_{max}))/2 \quad (13)$$

where, $t$ is the amount of time elapsed in a given game and $t_{max}$ is the game termination time. The final state of the evader, at any given time, is taken to be a weighted sum of the sensor information, and can be given as,

$$S(t) = t_f(W_L D_L + W_B D_B)/(W_L + W_B) \quad (14)$$

where, $W_L$ and $W_B$ represents the weights for Lidar sensor and boundary information respectively.

In a reinforcement framework, agent-environment interaction provides a reward $r$ for the agent to train. The reward function used in this paper embeds information about distance from the boundary, the location of observed opponents and time elapsed to capture all essential features of the environment. Let the number of defenders detected by the evader in the vicinity be $m$. In that case the reward due to defenders is given as,

$$W_i = (1 - (r_i/R_E^S)) \quad (15)$$

$$r_d = \sum_{i=0}^{m-1} W_i(V_{rel}^{max}.dt - (d_i^t - d_i^{t-1})) \quad (16)$$

where, $V_{rel}^{max} = V_E^{max} - V_B^{max}\cos(\theta_i)$ and $dt$ is the time step. Here, $V_E^{max}$ is the the velocity of the $i^{th}$ detected defender and $d_i^t$ distance from it at time $t$. And, $V_B^{max}\cos(\theta_i)$ is the defenders velocity towards the evader, as $\theta_i$ is the angle between heading of the defender and the line joining it to the evader. The formulation for $r_d$ represents the maximum possible distance the evader can travel away from the defender in a time step $dt$. The weight $W_i$ ensures more weight for the defenders closer to the evader. Similarly, with the information about the boundary, the evader interaction with the environment lead to a reward given by,

$$r_b = V_{rel}^{max}.dt - (d_n^{t-1} - d_n^t) \quad (17)$$

where, $d_n^t$ is the distance of the evader from the nearest boundary point at a given time $t$. The $r_b$ represents the maximum possible distance the evader can travel away from the defender in a time step $dt$. To get the final rewards the time factor, formulated in eqn. [13] is included to provide a negative reward of higher magnitude as the game proceeds with time. Thus, forcing the evader to learn to escape the confinement in minimum time. The final formulation of the reward function, can be given as,

$$r_f = t_f.[\{(1 - \sum_{i=0}^{m-1} W_i/(1 + m)).r_b + r_d \} \quad (18)$$

$R_f$ is used to generate the reward for the evader-environment interaction at any given time. The actor critic networks are then trained by minimizing the regression loss given by eqn. [9] and [10].
C. Scaffolding Reflection in Reinforcement Learning

As mentioned earlier, conventionally potential field method (PFM) has been the benchmark approach, that uses artificial forces between the agents for controlling the evaders in CEP [8]. However, in dynamic environments, a learning algorithm is expected to capture the context better than a heuristic algorithm. Thus, a reinforcement learning approach is proposed in this paper for evader’s motion control. But conventional RL consumes time for learning in CEP. Therefore a new framework called Scaffolding Reflection in Reinforcement Learning (SR2L) is developed. It uses the heuristic algorithm, that encodes the users perspective of the problem, as a scaffold for the evader while learning.

Fig. 2 shows the schematic diagram of the proposed SR2L framework. Here, the state action pair is decided by considering the action decision by both PFM ($a_p$) and AC ($a_r$) network along with their corresponding rewards ($r_p$ and $r_r$). During training, in every time step, the rewards are compared to quantify the performance of AC network against PFM. It is formulated as percentage of difference between the rewards and is given by,

$$D_f = \{(r_r - r_p)/|r_p + \epsilon|\}.100\%$$  \hspace{1cm} (19)

A scaffolding condition is established, which decides the final reward to be awarded to the actor. It is formulated as,

$$r = \begin{cases} r_r & \text{if } D_f \geq -\beta \\ r_r - |(r_p - r_r)| & \text{if } D_f < -\beta \end{cases}$$  \hspace{1cm} (20)

where $r$ is the final reward awarded to the actor and $\beta$ is a user defined constant between 0 to 100. Similarly the action sequence in every time step is determined by,

$$a = \begin{cases} a_r & \text{if } D_f \geq -\beta \\ a_p & \text{if } D_f < -\beta \end{cases}$$  \hspace{1cm} (21)

Thus, the experience tuple $<s, a, r, s'>$ is formed using the above formulation. This fastens the process of learning, as the probability of initial randomization of the actions space is minimized. The directions desired by the user (as PMF) gets embedded into the actor as the training starts. Thus allowing it to reflect upon its action, using PFM as a scaffold.

IV. Numerical Simulations

In this section, the working of the policy trained ($\pi*$) by SR2L for escaping the confinement region is presented. Then the convergence study to compare SR2L against conventional RL is done. Following that, the Monte-Carlo simulations study for the comparison between trained SR2L and PFM are presented.

A. SR2L for confinement escape problem

Consider a confinement region $A$, having rectangular boundary of dimension $200m \times 200m$. Let the number of defenders patrolling the area (n) be 30. The evader is initialized randomly within an area $\Omega$ of dimension $20m \times 20m$ near the origin. The defenders are initialized randomly within the confinement boundary and outside of $\Omega$. The evader’s initial velocity is taken to be zero, with the maximum velocity limit being $V_{E}^{\text{max}} = 15m/s$. The evaders are initialized with a random velocity between $V_{D}^{\text{min}} = 5m/s$ and $V_{D}^{\text{max}} = 10m/s$. The sensor radius of evader and defender is 15m and 10m, respectively. The sequence of actions by the evader in different time steps is given in Fig. 3a. Here, the green plot represents the evader’s path, and the blue arcs represent the Lidar point cloud data. The point cloud data representation, boundary information representation and the state of the evader at time step = 25 (Fig. 3a) is given in Fig. 3. The axis corresponds to the direction angle, considering the evaders heading as 0 deg. Here, the action space of dimension 2 is considered. This action space consists of the evader’s velocity along x and y axis for motion control. The evader’s trajectory in Fig. 3 shows the evader escaping from the nearest boundary point. In Fig. 3c the evader is shown to have crossed the line of $x = -100$, thus successfully escaping the confinement. As multiple defenders can detect the evader, start chasing the evader, it was able to change its course multiple times, as shown in Fig. 3c for avoiding capture while achieving a successful escape. It is also aided by the fact that the max speed ratio of $V_{E}^{\text{max}}/V_{D}^{\text{max}} > 1$ is considered. For visualization, the video of CEP using SR2L is provided in the following link: https://bit.ly/3nSrII

B. Convergence Analysis of SR2L and Conventional RL

The environment used in section IV-A is adopted for the convergence study. During training, for a given state $s$, the evader must learn to choose an action $a$ to maximize the reward $r$. The evader is trained using two different methods, a) Actor-Critic in conventional RL framework, b) Actor-Critic in the SR2L framework. In the former, the Actor-Critic is trained by using the reward generated by Eqn 18. Here, the timestep $dt = 0.1$ units and termination time $t^{\text{max}} = 300$ units is taken. The constants $K_{s} = 1, R^{g}_{S} = 40, d_{n}^{\text{max}} = 200$ and $\gamma = 0.001$ are considered. The weights $W_{L} = W_{B} = 1$ for the state generation are used. The convergence plot of this learning process is given in Fig. 3a. For the second case, same constant values are used. However, the action is chosen by using Eqn. 21, and the corresponding reward is awarded using Eqns. 18 & 20. The convergence plot
time step = 25.

(b) time step = 50

(c) time step = 80.

Fig. 3: A sequence of actions taken by the evader to escape the rectangular confinement region of dimensions $200m \times 200m$. The green trajectory represents the path followed by the evader, whereas the blue arcs represent the point cloud data.

Fig. 4: The state and individual data representation of Lidar and boundary information at $t = t_{max}/2$.

for this case is given in Fig. 5b. The figures show that the learning process using the conventional RL framework converges after approximately 1500 episodes. Whereas, in the case of SR2L, it converges after approximately 130 episodes. Thus, achieving a convergence that is 11 times faster than the conventional approach. A comparison between the performance of the trained policies of SR2L after 200 episodes ($\pi^*_sr$) and conventional RL after 1700 episodes ($\pi^*_rl$) was performed. The scenario mentioned in section IV-A was run for 100 episodes using the trained policies. The $\pi^*_rl$ resulted in a successful escape 88% of the times as compared to 100% in the case of $\pi^*_sr$. Here, the failure cases involve 8 cases of evader capture and 4 cases of evader exceeding the time limit. The above results show that SR2L helps in faster convergence with better generalization capabilities.

C. Monte-Carlo Performance Evaluation of SR2L

For Monte-Carlo simulation study, the same environment presented in the section IV-A is used. Simulation was conducted for evader using the SR2L policy and also using the potential field method. The simulation study was carried-out 1000 episodes with random initializations. The average time taken by both the evaders to escape confinement per 100 episodes is plotted in the Fig. 6a. It shows that the average time taken for escape using SR2L is always lower than that of PFM. The state information in SR2L uses time factor and distance to boundary, which help evader using SR2L policy to escape faster than PFM. During these episodes, the evader’s reward was also recorded for all 1000 episodes. The average reward achieved by both evaders per 100 episodes is plotted in Fig. 6b. As the PFM is used as a scaffold in the SR2L framework, the trained policy ($\pi^*$) always has a higher average reward for CEP. These results also reflect a learning algorithm’s ability to capture more features from the states than a handcrafted PFM algorithm.

For further evaluation, Monte-Carlo simulation was carried
with varying total number of defenders, the maximum speed ratio \( V' = V_{E_{\text{max}}} / V_{D_{\text{max}}} \) and the ratio of sensing radius \( R' = R_{E_{\text{max}}} / R_{D_{\text{max}}} \). The results have been tabulated and presented in Table I. It shows the percentage of successful escape in a corresponding scenarios along with the average time of escape. Consider the worst case scenario, where \( V' = 1 \) and \( R' = 1 \) is used, and 50 robots are patrolling the area. With 10m sensor radius, considering 20% of overlap of sensing area among the defenders, at any given time, 40% of the area is under the coverage of the defenders. Even in such a scenario, 77% of the time evader escapes successfully. Here, the failure cases include 16 cases of evader being captured and 7 cases of exceeding the time limit for escape.

The results shows that the evader trained using SR2L is able to escape with varying environmental parameters with different numbers of robots, thus highlighting its scalability.

V. Conclusions

This paper proposes the Scaffolding Reflection in Reinforcement Learning (SR2L) framework for an evader to escape a confinement region against multiple defenders. The defenders are considered to patrol the region without any communication among them. Upon detecting the evader, the defenders pursue the evader to capture it. A state representation consisting of information about the vicinity, boundary, and time elapsed is designed for the Actor-Critic network to extract essential features for CEP. The potential field method (PFM) is used as a scaffold to support and fasten the learning process. As SR2L considers a partially observable environment, it is computationally efficient. However, the issue of dimensionality can still arise because of the number of defenders. So, state representation is designed for the learning algorithm to capture the environment’s spatial features to avoid dimensionality issues. As the PFM is used as a scaffold for SR2L, the latter’s performance is more effective than the former. Also, the convergence study of SR2L against conventional RL shows the scaffolding reflection technique learns effectively in a shorter interval.

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