Novel Sensor Scheduling Scheme for Intruder Tracking in Energy Efficient Sensor Networks

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Abstract—We consider the problem of tracking an intruder using a network of wireless sensors. For tracking the intruder at each instant, the optimal number and the right configuration of sensors has to be powered. As powering the sensors consumes energy, there is a trade off between accurately tracking the position of the intruder at each instant and the energy consumption of sensors. This problem has been formulated in the framework of Partially Observable Markov Decision Process (POMDP) [1]. Even for the simplest model considered in [1], the curse of dimensionality renders the problem intractable. We formulate this problem with a suitable state-action space in the framework of POMDP and develop a reinforcement learning algorithm utilizing the Upper Confidence Tree Search (UCT) method to mitigate the state-action space explosion. Through simulations, we illustrate that our algorithm yields good performance and scales well with the increasing state and action space.

I. INTRODUCTION

The problem of detecting an intruder (Intrusion Detection (ID) problem) using a network of sensors arises in various applications like tracking the movement of wild animals in the forest, house/shop surveillance for safety and security and so on. In this problem, the objective of the ID system is to track one or more intruders moving in the field of a wireless sensor network (WSN). Typically, WSNs operate on limited power supply. This imposes a limitation on the number of sensors (energy budget) that can be switched ON over a time period when tracking the intruders and thus, constraints the maximum achievable tracking accuracy. Hence, the problem focussed in this paper is to propose a novel ID algorithm that respects such resource constraints.

We consider a variant of this problem in which an intruder is moving in a special network configuration, that is a sensor grid in which the battery operated sensors are placed in each block of the grid. At every time period, the intruder moves from one block to another according to a specified governing dynamics. The ID system decides to keep the sensors in some of these blocks ON in order to track the intruder. Whenever the intruder moves into a block where the sensor is ON, the position of the intruder gets recorded. Instead if he moves into a block where the sensor is OFF, then the intruder’s position will not be recorded for that time period. The challenge here is to decide on the optimal number and the right configuration of sensors to be powered ON in order to balance the conflicting objectives of minimizing the energy consumption of the network and maximizing the intruder tracking accuracy.

Significant body of research exists that proposes solutions to the ID problem. Due to space constraints, we will limit the discussion to the most relevant papers to our approach. In [2], the ID problem has been formulated as a partially observable Markov decision process (POMDP) and two heuristic solutions have been proposed. Note that solving the POMDP for optimal solution is computationally intractable and one often resorts to heuristic POMDP solution. In the first method, they have proposed Q_{MDP} with an assumption of observation-after-control, i.e., position of the intruder at any time period will be known to the system from the immediate next and future time periods. Under this assumption, they show that the problem can be decomposed into separate sub-problems where individual decisions can be arrived at for each sensor. Each sub-problem can be solved using policy iteration [3]. As the policy obtained is myopic in nature, [2] developed a point-based approximation method based on the idea of perseus [4]. The key idea behind this method is to find optimal action for a reachable set of simulated beliefs (see Section II) and uses the assumption that the intruder moves in a special path, i.e., the transition probability matrix has a special sparse structure rendering only a finite number of path configurations to be actually feasible.

In [1], first cost reduction solution (FCR) has been proposed with a simplifying assumption on the evolution of the belief vector and thus, it yields a sub-optimal policy. In [5], the previous work was extended by generalizing the models for object movement, sensing and tracking cost. In [6], a multi-timescale Q-Learning algorithm with function approximation has been developed to solve the intruder
detection problem. In general, Q-learning with function approximation is not known to converge to optimal policy. However, by separating the control from the policy evaluation step, it has been shown in [6] that their two timescale Q-learning algorithm converges. However, choosing the right features for function approximation poses a problem which directly affects the quality of solution.

In addition to the above mentioned POMDP model, many other frameworks have been considered in the literature. In [7], a region prediction sensor activation algorithm (PRSA) has been proposed where a subset of active nodes based on the position and velocity of the intruder is selected. Among the selected subset of nodes, the lowest number of essential nodes will be switched ON. In [8], a model in which sensor positions are arranged in the form of a polygon has been considered and an A-star algorithm was applied for selecting the optimal nodes in the polygon.

Our contribution in this paper is to apply general RL algorithms to solve the POMDP formulated in [2] that tackle both the aspects of state space and action space explosion in a novel way. Our algorithms do not make any assumptions on the structure of the network or the movement of the intruder and also do not use additional information at the controller.

The following summarizes our contributions:

- We propose three RL algorithms to achieve good intruder tracking performance
  - Our first algorithm $ID_TG$ is greedy, easy to implement and totally avoids the state and action space explosion. However, this simple algorithm does not yield good performance.
  - Monte Carlo Tree Search (MCTS) algorithm became popular in recent times [9] and can be applied to solve the problem of large state space. Our second algorithm $ID_MCTS$ uses MCTS idea to alleviate the state explosion problem. However, $ID_MCTS$ still suffers from the problem of action explosion.
  - Our final $ID_{\gamma_MCTS}$ algorithm combines the advantages of both of the above two algorithms to handle both the state and action space explosion problems while yielding good tracking performance.

II. POMDP FRAMEWORK FOR THE ID PROBLEM

Let us consider a sensor grid where sensors are placed, one on each block of the grid. The intruder moves from one block to another in the grid in each time period. The sensors that are kept ON in the grid send their observation whether the intruder was seen on that block to the central controller. Based on this information, the central controller finds the optimal action to be taken i.e., it decides how many and which sensors need to be switched ON in the next time period, and broadcasts this action to all the sensors in the network. This sequential decision making problem can be posed in the framework of Partially Observable Markov decision process (POMDP) [10].

We now formally present the POMDP formulation for the ID problem [2].

- Let $n$ denote the total number of sensors in the network.
- Let the actual position of the intruder at time $k$ be denoted as $s_k$.
- The stochastic matrix $P$ of dimension $(n+1) \times (n+1)$ models the actual transition probability of the intruder movement between various blocks. Note that the transition between states modeling the intruder movement for this POMDP does not depend on our decision or action, i.e., which sensors have been turned ON.
- Action Space : At time $k$, let $u_k$ denote the vector that indicates the decision on which sensors to be switched on for the next time period
  $$u_k = (u_{k,l})_{l=1,...,n} \in \{0,1\}^n,$$
  where 0 denotes the action to keep the sensor OFF and 1 denotes the action to keep the sensor ON. Here, $u_{k,l}$ denotes the decision for the $l$th sensor in the $k$th time period. Note that the number of actions is exponential in the number of sensors and thus leaving us with a large number of actions from which we need to decide.
- Observations: There can be three possibilities. If we track the position of the intruder, then the observation is the state of the system $s_k$ itself. In some cases, we may not be able to track the position of the intruder. We let $\epsilon$ to represent this situation. The final possibility is that the intruder may have moved out of the network. Let $\tau$ indicate this situation. We assume that if the intruder moves out of the network (i.e., observation = $\tau$) this information gets immediately known to the controller. So,
  $$o_{k+1} = \begin{cases} 
  s_{k+1}, & \text{if } s_{k+1} \neq \tau \text{ and } u_{k,s_{k+1}} = 1 \\
  \epsilon & \text{if } s_{k+1} \neq \tau \text{ and } u_{k,s_{k+1}} = 0 \\
  \tau & \text{if } s_{k+1} = \tau.
  \end{cases}$$

- The history or information content available at time $k$ is: $I_k = \{o_0, u_0, o_1, u_1, \ldots, o_k, u_k\}$.
- The optimal action is obtained from the optimal policy according to:
  $$u_k = \mu_k(I_k),$$
where $\mu_k$ denotes the optimal action selection function given the ‘information vector’ at time $k$.

- State Space: As the number of stages or the time slots increase, the size of history increases and thus, it becomes difficult to compute the optimal policy using finite memory. So we need to develop a different representation for the state space. We solve this problem with the help of belief vectors. The belief vector $p$ is an $(n + 1) \times 1$ vector, in which $p_k(l)$ indicates the probability of the intruder being at position $l$ at time $k$. This evolves as follows:

$$p_{k+1} = e_T \mathbb{I}_{\{s_{k+1} = T\}} + e_{s_{k+1}} \mathbb{I}_{\{u_{k+1}, s_{k+1} = 1\}} + [p_k P]\{j: u_{k+1}, j = 1\} \mathbb{I}_{\{u_{k+1}, s_{k+1} = 0\}},$$

where $e_i$ is the vector that represents 1 at position $i$ and 0 at other positions. The notation $|V|$ is the probability vector obtained by setting all components $V_i$, such that $i \in S$ to 0 and then normalizing this vector so that the sum of the components in $V$ is 1. This is to account that we did not track the position of intruder, so we are sure that intruder did not move to sensor positions which are switched on.

- We define the single stage cost model for the ID problem using two cost components. The system incurs unit cost, if we do not track the position of intruder at a given time period and 0, if we track the position. Let us define

$$T(s_k, u_k, s_{k+1}) = \mathbb{I}_{\{u_k, s_{k+1} = 0\}},$$

where $\mathbb{I}(\cdot)$ is the indicator function. This cost $T(s_k, u_k, s_{k+1})$ captures the fact whether intruder is tracked or not. The other cost component $C(s_k, u_k, s_{k+1})$ provides constraint on the number of sensors that can be kept awake, i.e.,

$$C(s_k, u_k, s_{k+1}) = \sum_{l=1}^{n} \mathbb{I}_{\{u_k, l = 1\}}.$$

The long-run objective is to minimize the average expected tracking error while satisfying the limit on the number of sensors to be ON (energy budget constraints):

$$\min_{u_k, k \geq 0} \lim_{n \to \infty} \frac{\mathbb{E}[\sum_{k=0}^{n} T(s_k, u_k, s_{k+1})]}{n}$$

subject to

$$\lim_{n \to \infty} \frac{\mathbb{E}[\sum_{k=0}^{n} C(s_k, u_k, s_{k+1})]}{n} \leq b,$$

where $\mathbb{E}[\cdot]$ denotes the Expectation over state transitions and $b$ specifies the energy budget (upper bound on the number of sensors that can be kept awake) in a time period.

- Cost Function: We modify the single-stage cost function to include the constraint as follows:

$$g(s_k, u_k, s_{k+1}) = T(s_k, u_k, s_{k+1}) + \lambda \times C(s_k, u_k, s_{k+1}),$$

where $\lambda \in [0, 1]$ is a suitable threshold for tracking error and budget constraints. If we set $\lambda$ to 0, it is similar to having unlimited budget, in which case all the sensors will be kept ON all the time. On the other hand, $\lambda = 1$ implies there is strict budget constraint, which case, all the sensors will be switched OFF.

In this way, by optimally tuning $\lambda$, the algorithm could support different levels of tracking error and average energy budget.

Now we have modeled the ID problem using the POMDP framework. The uncertainty in the state can be removed by treating belief vector as our new state. We now have all the ingredients for an MD and one would hope to utilize the standard dynamic programming methods like policy iteration and value iteration [11] for solving the MDP. However, these methods operate on finite state space whereas the possible belief vector, which forms the new state space for this problem is uncountably infinite. Therefore, finding an optimal policy for this problem by solving the MDP is intractable [11] leading us to focus on developing a suitable algorithm that can handle a large state and action space. This would ensure good tracking performance while meeting the energy budget constraints.

### III. Our ID Algorithms

In this section, we describe our RL algorithms.

#### A. Greedy Algorithm (ID, TG)

This is a simple greedy algorithm in which the top probable sensor positions the intruder might move to will be turned ON for tracking during each time period. The number of sensors that will be kept ON is decided based on a chosen parameter $\gamma$, where $\gamma \in (0, 1)$. The first step of this algorithm involves obtaining the approximate belief vector for the next time period. Note the belief vector gives the probability of the intruder reaching various possible positions in the next time period. In order to compute the belief vector, we use [3]. Then we select those positions in the belief vector that sum up to $\gamma$ starting from the highest probability value. We could view $\gamma$ as a minimum confidence index on tracking the position of intruder.

We can see that this algorithm is very easy to implement and at the same time solves the problem of state and action space explosions. However, at every instance, $\gamma$ chosen is constant and independent of the number of non-zero values in belief vector. Consider a scenario in which
the belief vector is ‘dense’. By ‘dense’, we mean that there are many non-zero probability positions in the belief vector whose values are very close to each other. Suppose we did not track the position of intruder in that time slot. Then, the belief vector grows further dense (see (3)). In this case, we would like to use a higher γ so that we could have more number of sensors ON and track the position of the intruder. Otherwise, the belief vector would grow more dense resulting in bad tracking accuracy. On the other hand, if the belief vector is sparse, then even a smaller γ would give better tracking. Also, we do not know, the best choice of γ for a given budget and the current belief. In summary, having a constant gamma value at every time period is not the right choice for optimal performance. However, the idea of using γ as a handle for deciding the actions instead of directly searching over the number and configurations of sensors will play a crucial role in solving the action space explosion problem in our proposed algorithm 1D_γ-MCTS.

Algorithm 1 ID_TG

1: n ← Number of sensors in the network.
2: γ ← predefined value entered by the user.
3: k = 0, p₀ ← Initial belief vector, tot_cost = 0.
4: procedure ID_POMDP
5: while Intruder is in the Network do
6:     ABV_{k+1} = p_k × P
7:     g = 0; u(k,l) = 0, ∀l = 1…n
8:     while g ≤ γ do
9:         l ← ABV{l} with maximum probability.
10:        u(k,l) = 1, g := g + ABV(i),
11:        Remove position l from ABV.
12:    end while
13:    tot_cost += get_cost(belief, action)
14:    Update Belief as in (3)
15:    k+= 1
16: end while
17: avg_cost = \frac{tot_cost}{k}
18: end procedure

B. Monte Carlo Tree Search (MCTS)

In this section for completeness, we first describe the idea of MCTS for determining the optimal decisions for an MDP and then we adapt this algorithm to the POMDP setting. For more details about the algorithm the reader is referred to [12]. MCTS has gathered a lot of attention in recent times due to its success in playing strategic games like GO [9]. The main idea behind this algorithm is to run multiple simulations (with the help of simulator placed at the controller) from the current state to determine the best action in each iteration. We begin with a single node where the node represents the current state. Then, we select an action for the given state using the Upper Confidence Bound for Trees (UCT) rule. The general UCT rule is given in [12] as follows:

\begin{equation}
UCT_{action} = \arg \max_j \hat{X}_j + C \times \sqrt{\frac{\log N/N_j}{N_j}} , \quad (8)
\end{equation}

where \( \hat{X}_j \) denotes the estimate of the average/discounted long-run reward (negative of the long-term cost) one obtains by selecting action \( j \) starting from the current state, \( N \) denotes the total number of runs so far and \( N_j \) corresponds to the total number of runs by selecting action \( j \).

In the beginning, all actions have 0 count, i.e., \( N_j = 0 \). Therefore, we can see that an unexplored action will have a higher probability of being selected on each simulation run. After all the actions have been explored, the action that has led to the highest reward collected, i.e, the term \( \hat{X}_j \) gets selected. In this manner it balances both exploration and exploitation. When an action is selected, we obtain the single stage reward/cost and a next state. Then, a new node and a new edge is added to the tree, where the edge represents the action we have chosen and the new node represents the next state obtained. We continue this construction, adding new nodes and edges to the tree till the desired depth. In this manner, we obtain a Monte-Carlo sample trajectory and a sample for the estimate of the long-run reward/cost. We could obtain multiple trajectories by trying out different actions (including the tried action) in the current state for getting better estimates of the long-run reward. This procedure is now repeated again from the root node till the timeout [12]. At the end of the timeout, we pick the action that has maximum long-run reward. This method helps in breaking the curse of dimensionality of the state space by sampling the state transitions instead of considering all possible state transitions to estimate long-run reward. If the exploration is done in an optimal manner, [12] has shown that the algorithm converges to the optimal policy.

1) 1D_MCTS Algorithm: In this algorithm, we run the MCTS [12] on our setting. That is, for the belief vector at time \( k \), we run the MCTS algorithm and obtain the action to be executed for the next time instant using the UCT action selection [8]. At each iteration of the algorithm, the position of the intruder needs to be known for the simulator to generate the next state. We can estimate it from the belief vector in two ways. The first method involves sampling a position from the belief vector according to its distribution at each iteration. The second approach selects the position with maximum probability at every iteration. The second approach is very natural and we employ it in our algorithm.
From the experiments, we observe that the algorithm increases the number of sensors that are kept ON in the subsequent intervals if it does not detect the position of the intruder for a large number of contiguous time periods. Similarly, as the intruder gets tracked continuously, the number of sensors that are kept ON in the subsequent time periods reduces.

As discussed earlier, this algorithm solves the problem of state explosion. However, the algorithm requires all the (exponential) number of actions (the different configuration of sensors out of $n$ block positions) to be tried out sufficient number of times before the timeout. There can be $2^n$ actions as $n$ is the total number of sensor position actions possible. As the size of network increases, the action space exponentially increases and it takes large amounts of time to execute all the actions due to which some actions might not be tried. Thus, the action we finally obtain at the end of the timeout will be ‘sub-optimal’. We overcome the main difficulty due to large action space by appropriately changing the action space (all possible sensor positions) of the POMDP to a discretized parameter $\gamma \in [0,1]$ that was fixed in the $ID_{_TG}$ algorithm and develop the final algorithm $ID_{\gamma_{-}MCTS}$ that solves the problems of both state and action explosions.

C. $ID_{\gamma_{-}MCTS}$ Algorithm

In the $ID_{\gamma_{-}MCTS}$ algorithm, we let the action space to be a predefined set of $\gamma$ values in the range 0 to 1 (with a uniform gap of 0.05). Note that the number of possible actions for this algorithm is constant unlike the exponential actions in the earlier algorithms in the literature. We run MCTS to obtain the optimal $\gamma$ value for the present belief vector. As we have discretized the action space, all the actions are chosen a sufficient number of times. The idea behind this construction is that it suffices to know how many sensors need to be kept awake in terms of $\gamma$ during each time period instead of explicitly knowing the exact configuration of the sensors. We could then use this value of $\gamma$ to select the top probable positions in the belief vectors as described in Algorithm 1. These sensor positions will be kept ON for the next time period. This process is repeated until the intruder moves out of the network. The complete $ID_{\gamma_{-}MCTS}$ algorithm is described in Algorithm 2.

As described above, Algorithm 3 imbibles the ideas of both $ID_{_TG}$ and $ID_{MCTS}$ and totally solves the problems of state and action explosions. Moreover, we observe that the $\gamma$ value at each time period is selected dynamically and is not kept constant, which is a significant drawback for the $ID_{_TG}$ algorithm.

From the experiments, we observe that in few cases the actual path of the intruder and the path that we are estimating diverge. This happens whenever the belief vector gets too dense and $\gamma$ selected is not very high. Then, we lose the position of the intruder and in this case, the belief vector grows more dense in the subsequent time periods. This results in the intruder not getting tracked for many contiguous time intervals and which affects the tracking accuracy. To overcome this problem, we introduce the restart mechanism. This involves switching on all the sensor positions that have non-zero probability whenever the belief vector has more than the threshold number of non-zero values. We observe this divergence problem occurs very rarely and thus the restart cost can be practically ignored.

Algorithm 2 $ID_{MCTS}$

1. Action Space - set of all $2^n$ configurations of sensors.
2. get action() - function to compute the optimal action for a given belief.
3. next position() : function to compute the next actual position of the intruder.
4. get cost() : It computes the single stage cost.
5. $k = 0$, tot_cost = 0
6. procedure MDP
7. while Object is within the Network do
8. $a_k = \text{get action}(p_k)$
9. $s_{k+1} = \text{next position}(s_k)$
10. $p_{k+1} \leftarrow$ Update the belief vector as in (3)
11. tot_cost += get_cost($s_k, a_k, s_{k+1}$), $k+1$
12. end while
13. end procedure
14. procedure get action(p)
15. while Time_Out $\geq$ 0 do
16. $s = \arg \max_s p(s)$
17. $MCTS(s, p, 1)$
18. end while
19. return arg min_s $\tilde{X}(p, a)$;
20. end procedure
21. procedure MCTS(s, p, depth)
22. if (depth $\geq$ MAXDEPTH ) return 0;
23. Select an action $a$ using the $UCT$ policy as in (8) (or any other action exploration strategies)
24. $s_{new} \sim \text{Simulator}(s)$
25. $p_{new} \leftarrow$ Update belief as in (3)
26. $Cost \leftarrow \text{get cost}(s, a, s_{new})$
27. $\alpha * MCTS(s_{new}, p_{new}, \text{depth} + 1)$
28. $\tilde{X}(p,a) += (Cost - \tilde{X}(p,a))/N(p,a)$
29. $N(p,a) += 1$
30. end procedure

IV. Experiments and Results

We considered three different configurations of the sensor network. In our first setting, we considered a 1-
In our experiments, we run our algorithms for different values of \( \lambda \) and choose the \( \lambda \) value that meets the given budget constraints (the average number of sensors awake) and also has the lowest tracking error. We plot the average number of sensors awake and its corresponding tracking error. Note that for different algorithms different values of \( \lambda \) could lead to the same average number of sensors. We do not plot the results for the ID\_TG algorithm as it does not yield good tracking performance owing to its static nature. However, the idea of choosing \( \gamma \) instead of the number and configuration of sensors for the action space gives significant computational savings in the ID\_\gamma\_MCTS algorithm. As the size of the sensor network is large in the second and third settings, our ID\_MCTS algorithm doesn’t scale up owing to the action space explosion. Thus, we do not show results for ID\_MCTS algorithm in the second and third plots and compare mainly our ID\_\gamma\_MCTS algorithm against Q_{MDP} given in [2]. All the results for ID\_\gamma\_MCTS algorithm are averaged across 10 simulation runs of the experiment.

![Figure 1: 1D Sensor Network with 41 sensors](image)

In the Figure 1, we observe that ID\_\gamma\_MCTS outperforms ID\_MCTS. This is because the cardinality of the action space in ID\_MCTS is 127 whereas in ID\_\gamma\_MCTS the cardinality is 20. However, we can see that Q_{MDP} performs better than both our proposed algorithms. This is mainly because of the observation after control assumption (that we do not impose in our setting) and partly due to the small size of the sensor network. As noted earlier, this assumption imposes a severe constraint and we don’t make this assumption. Thus, it is noteworthy that our algorithm performs well even without this assumption. In the Figure 2, we observe that the performance of ID\_\gamma\_MCTS in comparison with Q_{MDP} has improved over a 2D sensor network. In fact, it performs better than Q_{MDP} until the average number of time periods.

Algorithm 3 ID\_\gamma\_MCTS

1: Action\_Space : Discrete set of gamma values entered by user
2: \text{get}_\gamma() - computes the best gamma value for a given belief
3: \text{get}_\gamma() - sets the action for the given belief and \( \gamma \) value
4: \( k = 0, \) tot\_cost = 0
5: \( s_0 \) ← Initial position
6: \( p_0 \) ← Initial belief
7: procedure MDP
8: \hspace{1em} while \ Object is within the Network do
9: \hspace{2em} \( \gamma = \text{get}_\gamma(p_k) \)
10: \hspace{2em} \( a_k = \text{get}_\gamma(p_k, \gamma) \)
11: \hspace{2em} \( s_{k+1} = \text{next\_Position}(s_k) \)
12: \hspace{2em} \( p_{k+1} \leftarrow \text{Update belief as in } (3) \)
13: \hspace{2em} \( \text{tot\_cost}+ = \text{get}_\gamma(s_k, a_k, s_{k+1}) \)
14: \hspace{1em} end while
15: end procedure

dimensional sensor network with 41 sensors with probability transition matrix similar to the one considered in [2]. At the start of the experiment, the intruder is placed at the center of the network with the movement constraint that he could either move 3 positions left or 3 positions right from the current position. In the second setting, we ran our algorithms on a two-dimensional sensor grid of dimension 8 × 8. The feasible movements of the intruder are left, right, down, up and along all the diagonals. In our final experiment, we ran our algorithms on 2-D grid with dimension 16 × 16. In both the second and third settings, we generated the transition probability matrix randomly.

We averaged the results of our simulations over 30 time periods. The MCTS algorithm was run for 500 iterations in every time period. We computed the long-term cost in the experiments as the discounted sum of single-stage costs for learning the decisions. Note that by choosing the discount factor close to 1, the actions learned for the long-run discounted cost setting will be similar to the actions learned for the long-run average cost setting. We have set the discount factor \( \alpha = 0.9 \). For the ID\_\gamma\_MCTS algorithm, we chose the \( \gamma \) parameter corresponding to the actions by discretizing the interval \([0, 1]\) in steps of 0.05. Thus, there are totally 20 discretized actions in the action space. In the plots, the X-axis corresponds to the average number of sensors awake which is computed as the ratio of the total number of sensors switched ON during the run of the algorithm and the total number of time periods and the Y-axis corresponds to the average tracking error which is obtained as the ratio of the number of time periods in which the intruder is not tracked and the total number of time periods.
of sensors is 3. In the Figure 3, we see the performance of the $ID_{\gamma\text{MCTS}}$ algorithm has further improved. To conclude, the $ID_{\gamma\text{MCTS}}$ performs better than other algorithms when the sensor network become very large which is typical in most of the practical applications.

V. CONCLUSION

In this work, we proposed three algorithms for solving the problem of intruder detection under energy budget constraints. Our first algorithm $ID_{\text{TG}}$ is greedy, simple and easy to implement. However, due to its static nature, it does not yield good performance. Our second ($ID_{\text{MCTS}}$) algorithm is a suitable adaptation of the MCTS algorithm for the ID problem. This solves the problem of state space explosion problem, however, the action space is still large and remains to be handled. Our final algorithm ($ID_{\gamma\text{MCTS}}$) combines ideas from our earlier two algorithms and totally solves both the state and action space explosion problem and this algorithm is the first of its kind for the ID problem. In our MCTS based algorithms, as we only need to account for the belief vectors that are encountered during the run, which are finite, holds the key to mitigating the state space explosion. Further, as we suitably modify the action space using predefined set of $\gamma$ values the action space explosion is also effectively handled. From simulations, we observed that the $ID_{\gamma\text{MCTS}}$ algorithm is our best algorithm when the network size becomes large and performs well without making any assumption on the intruder movement or the intruder position information. In the future, we would like to extend this problem when multiple intruders are moving in the sensor network. In this scenario, we could consider the possibility of more than one intruder moving in the network with possibly different transition probabilities and their movements could be correlated as well. Our objective would be to track the positions of as many intruders as possible satisfying energy budget constraints.

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REFERENCES

[1] J. Fuemmeler and V. Veeravalli, “Smart sleeping policies for energy efficient tracking in sensor networks,” IEEE Transactions on Signal Processing, vol. 56(5), pp. 2091–2101, 2008.
[2] G. K. Atia, V. V. Veeravalli, J. Fuemmeler et al., “Sensor scheduling for energy-efficient target tracking in sensor networks,” Signal Processing, IEEE Transactions on, vol. 59, no. 10, pp. 4923–4937, 2011.
[3] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction. MIT press Cambridge, 1998, vol. 1, no. 1.
[4] M. T. Spaan and N. Vlassis, “Perseus: Randomized point-based value iteration for pomdps,” Journal of artificial intelligence research, vol. 24, pp. 195–220, 2005.
[5] J. A. Fuemmeler, G. K. Atia, and V. V. Veeravalli, “Sleep control for tracking in sensor networks,” IEEE Transactions on Signal Processing, vol. 59, no. 9, pp. 4354–4366, 2011.
[6] L. Prashanth, A. Chatterjee, and S. Bhattacharjee, “Two timescale convergent q-learning for sleep-scheduling in wireless sensor networks,” Wireless Networks, vol. 20, no. 8, pp. 2589–2604, 2014.
[7] W. Zhou, W. Shi, X. Wang, and K. Wang, “Adaptive sensor activation algorithm for target tracking in wireless sensor networks,” International Journal of Distributed Sensor Networks, vol. 2012, 2012.
[8] A. Pawar and S. Nagstilak, “Energy efficient target tracking scheme for wireless sensor networks,” International Journal of Science and Research, 2013.
[9] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. Van Den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot et al., “Mastering the game of Go with deep neural networks and tree search,” Nature, vol. 529, no. 7587, pp. 484–489, 2016.
[10] M. T. Spaan, “Partially Observable Markov Decision Processes,” in Reinforcement Learning. Springer, 2012, pp. 387–414.
[11] D. P. Bertsekas, Dynamic Programming and Optimal Control. Athena Scientific Belmont, MA, 1995, vol. 1, no. 2.
[12] D. Silver and J. Veness, “Monte-carlo planning in large POMDPs,” in Advances in neural information processing systems, 2010, pp. 2164–2172.