Multiple Pursuers TrailMax Algorithm for Dynamic Environments

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Abstract: Multi-agent multi-target search problems, where the targets are capable of movement, require sophisticated algorithms for near-optimal performance. While there are several algorithms for agent control, comparatively less attention has been paid to near-optimal target behaviours. Here, a state-of-the-art algorithm for targets to avoid a single agent called TrailMax has been adapted to work within a multiple agents and multiple targets framework. The aim of the presented algorithm is to make the targets avoid capture as long as possible, if possible until timeout. Empirical analysis is performed on grid-based gaming benchmarks. The results suggest that Multiple Pursuers TrailMax reduces the agent success rate by up to 15% as compared to several previously used target control algorithms and increases the time until capture in successful runs.

1 INTRODUCTION

Search algorithms have been developed and studied for a long time. The basic scenario is that of a single agent that is tasked with finding a target or goal state on a graph within minimal time. Various assumptions of this scenario can be relaxed, leading to more difficult problems: there can be several agents that need to coordinate their search, there can be multiple targets, all of which need to be caught, and targets can move on the graph over time rather than be in a fixed position.

Many suitable algorithms have been proposed for pursuing agents in the domains of video and computer games, robotics, warehouses (Li et al., 2020), and military and surveillance applications (Panait & Luke, 2005). Some of these algorithms are for single agent, such as MTS (Ishida, 1992), D* Lite (Koenig & Likhachev, 2002) or RTTES (Undeger & Polat, 2007) and some are multi-agent, for example, FAR (Wang & Botea, 2008), WHCA* (Silver, 2005), CBS (Sharon, Stern, Felner, & Sturtevant, 2015) and MAMT (Goldenberg, Kovarsky, Wu, & Schaeffer, 2003). These algorithms aim to find the shortest path to the target location(s). While the shortest path is important, the run time is essential, too, as considered by real-time heuristic algorithms (Loh & Prakash, 2009).

For scenarios with moving targets, the target algorithms also play an essential role in developing multi-agent scenarios, but they are less studied. The goal of such algorithms is to evade capture as long as possible.

Consider a pursuit and evasion game, where agents could be humans or computer controlled. To make the game more interesting, intriguing, and challenging, the targets need to behave intelligently. Therefore, good target algorithms are an essential factor of improving the gaming experience.

Existing target algorithms usually have strategies such as maximising the escaping distance (Xie, Botea, & Kishimoto, 2017), random movements to a selected, unblocked positions in order to evade from the capturer (Pellier, Fiorino, & Métivier, 2014) or, in a state of the art approach called TrailMax, maximising the survival time in the environment (Moldenhauer & Sturtevant, 2009).

Multi-agent path finding (MAPF) problems have been analysed in detail in the literature (Sigurdson,

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Bulitko, Yeoh, Hernández, & Koenig, 2018), and are known to be NP-hard (Li et al., 2020). As an example of such a problem, in a video game, all non-player agents may need to navigate from a starting location to the goal location on a conflict free route in a static or dynamic environment (Chouhan & Niyogi, 2017).

Good algorithms for moving targets can make the empirical study of MAPF problems more meaningful and challenging. So how can we improve on existing ones? This paper introduces an algorithm based on TrailMax that can be used for multiple moving targets to escape from multiple agents in a dynamic environment.

In the remaining parts of this paper, Section 2 presents the related work. Section 3 describes the new approach to the problem. Empirical comparisons are described in Section 4, and conclusion is derived in Section 5.

2 RELATED WORK

This section introduces several existing target algorithms in the literature. The following is a brief description of each algorithm.

2.1 Target Algorithms

Although there is plenty of research in the literature emphasising algorithms for pursuing agents, there are few studies that are conducted on algorithms for mobile targets. A classic example is the A* algorithm, which is implemented for many pursuing agent and target algorithms (Sigurdson et al., 2018).

2.1.1 TrailMax

TrailMax is a strategy-based algorithm that generates a path for a target considering the pursuing agent's possible moves, i.e. it efficiently computes possible routes by expanding its position nodes and agent's nodes simultaneously (Moldenhauer & Sturtevant, 2009). The aim of the TrailMax algorithm is to make the targets stay longer by maximising the capture time. To compute a path, an escape route that maximises the intersection point, it checks the best cost of the neighbouring states against the pursuer's costs and expands nodes accordingly. The algorithm expands nodes that are not yet expanded, not in the target's list and not in the pursuer's list. The node with the best cost is added to the target's list, which would generate the path afterwards.

It is a state-of-the-art target strategy algorithm that performs the best against pursuing agents, aiming to make the targets less catchable or more difficult to be caught (Xie et al., 2017).

2.1.2 Minimax

When used as the target algorithm, it runs an adversarial search that alternates moves between the agents and the target, where the agent gets closer to the target state and the target distances itself from the pursuing agent's state. To make the algorithm faster, Minimax is run with alpha-beta pruning search, where alpha (α) and beta (β) are constantly updated to avoid the exploration of suboptimal branches (Bulitko & Sturtevant, 2006). The used depth is 5, i.e., the outcomes after at most 5 moves of each party are considered.

2.1.3 Dynamic Abstract Minimax

Dynamic Abstract Minimax (DAM) is a target algorithm that finds a relevant state on the map environment and directs the target using Minimax with alpha-beta pruning in an abstract space. The search starts on the highest level of abstraction, an abstract space created from the original space. If there is a path, then an escape route is computed using PRA* (see Section 2.2). If the target cannot escape and there is no available move to avoid the capture on the selected abstract space, then the level of abstraction is decreased and the whole process repeats until the target can successfully run away from being caught (Bulitko & Sturtevant, 2006). The used depth is 5.

2.1.4 Simple Flee

Simple Flee (SF) is another algorithm that can be used by targets to escape from the pursuing agents (Isaza, Lu, Bulitko, & Greiner, 2008). The SF algorithm works as follows. In the beginning of the search, the target identifies some random locations on the map. When the target starts moving, it navigates to the furthest location away from the pursuers. To disorient the pursuing agents, the direction towards the selected location changes in every five steps, and if it is the furthest location, it keeps moving. The number of locations on the map and the number of steps before the change are the parameters of the algorithm.

2.2 Pursuing Algorithm

This study sets out to develop a new multiple target algorithm. Therefore, this part of the section introduces only one algorithm for pursuing agents, which will be used in the experiments.

Partial-Refinement A* (PRA*) is an algorithm that reduces the cost of search by generating a path on an abstract level of the search space. These abstracted spaces (graphs) are built from the grid map. The abstract level is selected dynamically. The A* algorithm is then used to run a search with sub-goals on the abstract graph. The abstract path creates a corridor of states in the actual search space, through which the optimal path is found .

This is a widely used approach and its variations have been described with different search techniques (Sturtevant, Sigurdson, Taylor, & Gibson, 2019).

3 PROPOSED APPROACH

In the following section, a new target algorithm is described. First, the motivation will be given for the algorithm. The pseudo code (see Figure 1) provides more details.

When the problem was described in Section 1, it was stated that a smart target algorithm is very useful to have. In the simple scenarios where one agent pursues a target, the target would know from which agent it needs to escape, as there is only one. Some of the strategies to run away from the agent have been discussed in the previous sections. But if we consider a situation where multiple targets need to escape from the current state and move to the safest destination in the dynamic environment, how would targets know which agent they need to avoid for a successful run?

Although the TrailMax algorithm, as introduced in Section 2.1.1, is the state-of-the-art algorithm, it has been designed to work with only one agent, meaning a target does not have any strategy to escape from one pursuer and avoid another approaching pursuer at the same time.

For this particular reason, a target algorithm that would be able to identify approaching multiple agents and escape from all pursuers, a novel algorithm, called Multiple Pursuers TrailMax (MPTM), is developed.

The MPTM algorithm uses a similar methodology as TrailMax but enhanced for MAPF problems. There are two important reasons for implementing MPTM algorithm in MAPF problems. First, it can identify the state location of other targets and collaborate with them. Second, it can ensure the escape not only from one pursuing agent, but from any approaching evading agents. Here the focus is on the second issue.

The pseudo code for the MPTM algorithm is depicted in Figure 1. First, the current locations of all pursuers and targets need to be initialised. The next step is to sort all players according to their role and insert into the relevant lists, all pursuers to the *pursuer_node_list* and a target to the *target_node_list*. At this point all players will have a cumulative cost of zero. To make it easier to follow the code, each movement cost will be equal to one, unless it is in wait action, then it is zero. This is with an assumption that there is no octile distance.

Since this is the target algorithm, it starts first to check if there are any target nodes in the *target_node_list*. Then, it finds the best cumulative cost *c*, the highest value, for target and pursuer at line 7 and 8. If the c_t is lower or equal to the c_a, then the target expands its nodes. The expansion of nodes is computed simultaneously for target and pursuing agents. During the expansion of nodes, each side marks nodes as visited and insert into the closed lists, line 12 and 20.

The main part of this algorithm are the lines in between 13-22, where each pursuer loops through its state and expands its nodes independently from other pursuers. The closed nodes list for the target is reversed to identify the route. This expansion goes to the point where one of the pursuing agents occupies the node of the target.

```
 1: function MultiplePursuersTrailMax()
 2:   initialise position for all pursuers and target
 3:   add target to target_node_list
 4:   add pursuers to pursuer_node_list
 5:   initial cumulative cost c ← 0 for all pursuers, targets
 6:     while target_node_list not empty do
 7:       $c_t$ ← best c on target_node_list
 8:       $c_a$ ← best c on pursuer_node_list
 9:       if ($c_t \le c_a$) then
10:         expand target nodes
11:         if node not in target_closed and pursuer_closed
12:           insert node into target_closed
13:       else
14:         for each $p_i$ of players do
15:           get state $s_i$ for $p_i$
16:           if (pursuer)
17:             $c_a$ ← best c on pursuer_node_list
18:             expand pursuer nodes
19:             if node not already in pursuer_closed
20:               insert node into pursuer_closed
21:             end if
22:           end if
23:         end for
24:       end if
25:     end while
26:
27:   generate target_path
28:     reverse target_closed
29:   return target_path
30: end function
```

Figure 1: Pseudo code for the MPTM algorithm.

For multiple targets, the algorithm is run on each target, and normally, each will get a different outcome based on their location. The result will be the same if they are all in the same state. Even if the starting position is different, the targets could join their path if that is the optimal option.

4 EMPIRICAL EVALUATION

In this section the empirical results will be presented to demonstrate the efficiency of the proposed algorithm. First, the experimental setup will be described, then, performance results of the MPTM algorithm described in Section 3 will be reported.

4.1 Experimental Setup

For better comparability, standardised grid-based maps from the commercial game industry are used as a benchmark (Stern et al., 2019). The environments used are four maps from Baldur's Gate video game as shown in Table 1. Within the experiments, these maps are used with a four-connected grid and impassable obstacles. Figure 2 displays a sample map used for the experiments, where black coloured spaces are the obstacles, and the white space is a traversable area. The maps were chosen based on the presence of obstacles and difficulty of navigation. The movement directions could be up, down, left and right with a cost of one each. That said, the approach should work with different moving costs as well.

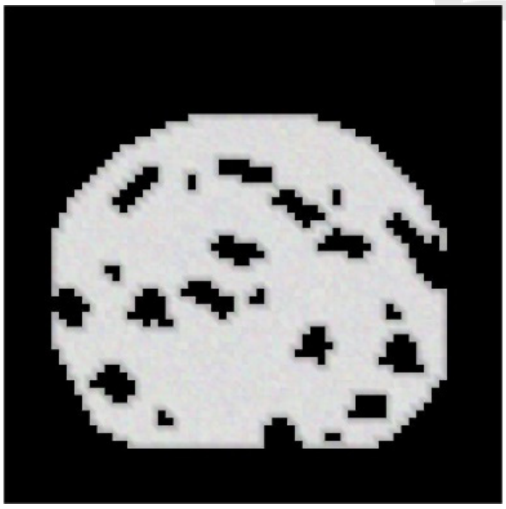


Figure 2: The experimented sample map (AR0607SR) used in the Baldur's Gate video game.

Table 1: The name of testbeds for the experiments with their height and width sizes.

Map names	Height x Width
AR0607SR	54x60
AR0514SR	64x64
AR0313SR	64x60
AR0417SR	54x52

The scenario chosen for the first tests is to have two targets and twice the number of pursuing agents. The second set of tests has the number of targets increased by one. The last configuration increases pursuing agent number to six versus three targets. All players are placed at different pre-selected random locations on each map. Altogether there were five different sets of starting positions. Only the first set has all pursuers in the same location and all targets in the same location, and targets are positioned in far distance from pursuers. This helps to analyse the behaviour of the algorithms.

Each configuration runs 30 times. The implementation of the simulation (Isaza et al., 2008) is developed using C++. The simulation was developed for a single target scenario and it was modified so that the tasks with multiple targets and assignment strategy for pursuing agents could be tested. The results were obtained using a Linux machine on Intel Core i7 with 1.9 GHz CPU and RAM with 40 GB.

4.2 Experimental Results

The section below reports the results from the experiments. Performance analysis is conducted with respect to two key indicators; (i) the number of steps taken for each target algorithm before being caught and (ii) its success rate. Both of the measurements are averaged considering all targets.

During the experiments, some pursuers could catch one target but miss the second one, and because the search is not finished yet, the chase continues. Success is achieved when both targets are caught, and the number of steps until all targets have been caught is recorded.

4.2.1 Pathfinding Cost

To evaluate the MPTM algorithm the comparison with SF and Minimax is displayed in Table 2. This measures the performance in terms of number of steps for all targets. The numbers indicate the means of steps by target algorithms per map.

It is seen from Table 2 that the proposed target algorithm offers much longer stay on the maps. This

Table 2: The average number of steps for each target algorithm per map for each set of configurations. Larger number is better as it avoids the capture from the pursuing agents.

	SF	Minimax	MPTM
	4 pursuers versus 2 targets		
AR0607SR	66.59	139.01	206.83
AR0514SR	46.55	62.04	142.82
AR0313SR	57.61	116.07	317.66
AR0417SR	46.32	173.16	260.52
	4 pursuers versus 3 targets		
AR0607SR	78.21	181.06	331.61
AR0514SR	61.68	87.09	153.13
AR0313SR	65.99	139.84	344.91
AR0417SR	50.81	178.42	228.92
	6 pursuers versus 3 targets		
AR0607SR	72.76	137.85	325.59
AR0514SR	66.59	85.33	88.55
AR0313SR	62.45	133.57	237.05
AR0417SR	47.82	171.07	197.83

indicates that it avoids capture and demonstrates smarter decisions. The higher number is better.

In the scenario, when the target number increases to three versus four pursuing agents, usually the targets manage to avoid capture longer in comparison with the first set of tests. In the cases where the number of pursuing agents are increased to six, 6 pursuers versus 3 targets, this predominance gives greater advantage to the pursuers and makes it difficult for targets to escape. Therefore, targets might get caught quicker.

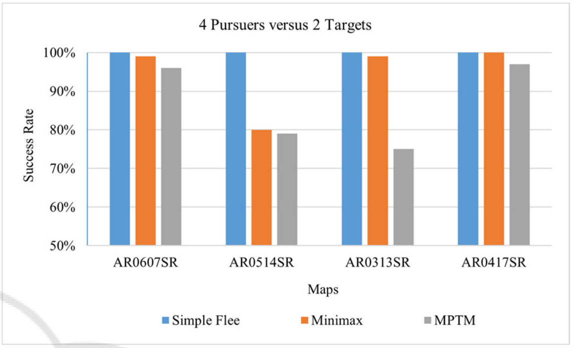
The evidence shows that the new MPTM algorithm outperforms SF and Minimax algorithms in number of steps in all test configurations.

4.2.2 Success Rate

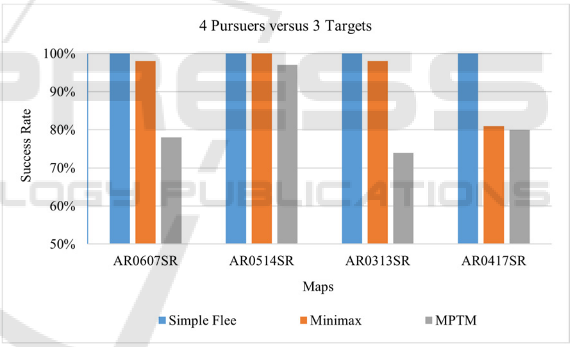
Success for the agents is achieved when a pursuing agent gets to the position of the target. In the multi-target scenarios, success is achieved when all targets have been captured. For the target(s), success is the absence of agent success. The success of the target algorithm is shown in Figure 3. There are three different graphs based on the number of players that are set for each test configuration.

From these graphs in Figure 3, the SF algorithm performs the worst, and it always gets caught by pursuing agents. Minimax shows better results in comparison with SF, although it has the cases where it gets caught 100%. Minimax is slightly worse than the MPTM algorithm on the AR0514SR map (4 vs 2) and on the AR0417SR map (4 vs 3) but performs better and escape longer only on one occasion, the AR0417SR map (6 vs 3). It is possible to say, the MPTM algorithm performs better than Minimax in most of the configurations and displays excellent results in some of these, but on the AR0417SR map with six pursuers and three targets, it performs approximately equal to Minimax.

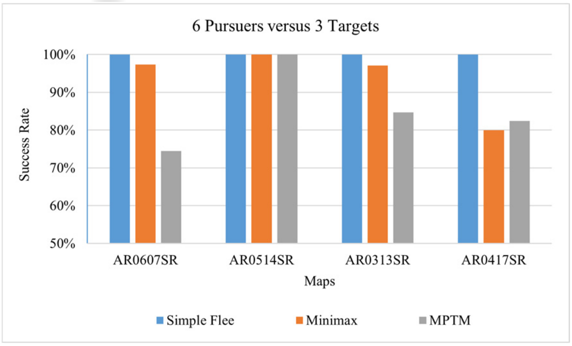
The behaviour of the MPTM algorithm is better on the maps that have obstacles that could be navigated around, for example the map illustrated in Figure 2. These types of maps may be suitable for adaptive target algorithms as they offer opportunities for escape but may be difficult for the pursuing agent



(a)



(b)



(c)

Figure 3: The performance rate of success for SF, Minimax and MPTM target algorithms, lower is better. (a) displays the results for 4 pursuers versus 2 targets, (b) is for 4 pursuers versus 3 targets and (c) is for 6 pursuers versus 3 targets.

algorithms if they do not have strategies such as the trap strategy (John, Prakash, & Chaudhari, 2008). The maps AR0514SR and AR0417SR have dead-ends or blind alleys and thus make it more difficult to find an escape route, leading to lower target performance on these maps.

The results clearly show that the new target algorithm, MPTM, performs far better in all of these simulations on the gaming maps used for benchmarking.

With the better algorithms, pursuing agents sometimes fail to catch the targets although these are outnumbered. They might catch one target but fail to catch the other, or keep following the target, or end in a deadlock until timeout.

The result of this study indicates that the MPTM algorithm exceeds expectations and, on average over all maps, shows a success rate 9% and 15% better then Minimax and SF, respectively.

5 CONCLUSION AND FUTURE WORK

The aim of this paper was to develop and study a target algorithm in MAPF problems. There have been many interesting studies done on search algorithms and among of them are solutions to the MAPF frameworks. Only several studies have been conducted on target algorithms, especially in the area where there are multiple targets.

The investigation shows that TrailMax is a successful algorithm for control of targets if extended for dealing with multiple agents. This study proposes amendments, first time, to TrailMax strategy algorithm as a state-of-the-art approach modifying and enhancing its scope to meet the criteria for multiple targets in the dynamic environment.

This new MPTM algorithm is applicable to moving targets and the success of having a smart method makes fast pursuing search algorithms to timeout. The results of this study demonstrate that the target algorithms are equally important in comparison to pursuer algorithms, and that makes the search more challenging and interesting.

Future studies should also look at computation time and how it could be improved. A more systematic approach would also study how the algorithm behaves on different testbeds and with different agent configurations, including those with a larger number of players. The comparison with other pursuing multi-agent algorithms would be useful.

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