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Capturing an Unknown Moving Target in Unknown Territory using Vision & Coordination

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Abstract**—**In this paper we present an extension to Vision Based LRTA* (VLRTA*) known as Vision Based Moving Target Search (VMTS) for capturing unknown moving target in unknown territory with randomly generated obstacles. Target position is unknown to the agents and they cannot predict its position using any probability method. Agents have omni directional vision but can see in one direction at some point in time. Agent's vision will be blocked by the obstacles in the search space so agent can not see through the obstacles. Proposed algorithm is evaluated on large number of scenarios. Scenarios include grids of sizes from 10x10 to 100x100. Grids had obstacles randomly placed, occupying 0% to 50%, in increments of 10%, of the search space. Experiments used 2 to 9 agents for each randomly generated maze with same obstacle ratio. Observed results suggests that VMTS is effective in locate target time, solution quality and virtual target. In addition, VMTS becomes more efficient if the number of agents is increased with proportion to obstacle ratio.

Keywords**—**Vision, MTS, Unknown Target, Coordination, VMTS, Multi-Agent.

I. Introduction

AGENT is a computational system which lives long and has goals, sensors, effectors and decides autonomously which action to take in which situation to maximize progress towards achieving its goal. In offline search algorithms such as A*, agent executes the complete search before actually taking a step towards the goal. In these algorithms, agent(s) examine various paths towards the goal state before they follow the best one. However, Real Time Search algorithms are used for problems where agents are interacting with initially unknown environment but with known target position. These path planning problems are interesting because they are different from traditional offline algorithms being dynamic in nature. Real time search makes decision within time limits and commits its decision towards real situation. Several extensions to real-time search have been studied in recent years and few are proposed in [2,3,4].

Moving Target Search (MTS) is a real time search algorithm, which is a generalization of LRTA*, for reaching the target that changes position over time [6]. Korf and Ishida proved that if the agent is moving faster than the target, the algorithm will guarantee that one of the agents will eventually reach the target in a connected problem space.

The efficiency of the real time search algorithms in successive trails may be improved since these algorithms can use the new heuristic values present at the nodes in the search tree. In some learning algorithms such as Learning Real Time A* (LRTA*) search where the target is static these heuristic values converge eventually to the optimal ones. In MTS where the target is moving, these values converge eventually to optimal ones if the target movement is controlled not random [6].

Most of the proposed real time search algorithms work for single agent with single known target. Various extensions to these algorithms were proposed using multiple agents involved in the search to achieve a common target [12,13,14]. Each agent chooses its move independently and do not coordinate there actions with each other so multiple agents may search the same path redundantly. Many coordination schemes for these real time search algorithms have been proposed which lead to better search time and solution quality [5,9].

In this paper, we have proposed an extension to VLRTA* known as Vision Based Moving Target Search (VMTS) for capturing unknown moving target in unknown territory with obstacles. In unknown environments, the agent vision has to be decided in run-time because there is no prior information about the target. In this environment, the agent should be able to take movement decisions autonomously. Furthermore, when the target is also moving the task becomes much harder, as the target may be visible at a point in time and then become invisible afterwards because of hiding behind the obstacles.

The main purpose of this paper is to show how new vision technique can greatly improve the efficiency of search algorithms in dynamic environment. Proposed vision technique has been successfully tested on large number of scenarios with different combinations like different maze sizes, varying obstacle ratio and varying number of agents.

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Since each agent tries to explore distinct unknown spaces; by increasing the number of agents in the search we have more chances to find and reach target in lesser time. Further, solution length measured in terms of search space states will also be reduced. Doing various experiments we have shown that as we increase the number of agents proportional to obstacle ratio, VMTS solution quality as well as target search time gets better and better.

Structure of the paper is as follows. Related work is discussed in section II. Section 3 contains the details of VMTS Algorithm, the modeling of agent and the coordination mechanism used in VMTS is discussed. Section IV describes VMTS framework. Section V critically analyzes the performance of VMTS in the randomly generated mazes. In Section VI conclusion and work future will be presented.

II. Related Work

The problem of searching a moving target has been worked out by many researchers from computer science and operation research disciplines. Various extensions of these already exist because of diverse nature of the problem. Original moving target search in computer science was proposed by [6], where the problem space was represented as connected graph. Notion of commitment and deliberation was introduced for improving efficiency of moving target search [7].

Moving target search is basically a single agent search algorithm but in [8] it has been extended for multi agent domain; where multiple agents are cooperatively trying to achieve their moving target.

Agents can better perform if they coordinate there actions with each other while trying to achieve the goal state. Umar and Kiran in [5] have used colors for coordination among agents. All the extensions of MTS proposed so for work for known target but several techniques have been developed for agents' visualization. Tan in [11] investigated learning based on low-level communication in the context of the predator-prey domain. Each predator has a limited visual field of some predefined depth. Busquets in [10] designed a vision based navigation approach for unknown environment using a fuzzy set based approach.

In this paper, we have extended Vision Based Learning Real Time A* to work with unknown moving target instead of static unknown target; like VLRTA* agent's have human like vision for finding target.

III. Vision Based MTS (VMTS)

Vision Based Moving Target Search algorithm is an extension of VLRTA* [1] where as the target is moving in this case. Like VLRTA* Algorithm each agent has an infinite vision and its vision can be blocked by obstacles in the search space. Agents coordinate their vision with environmental agent which has global view of the search space.

VMTS repeats the following first three steps until the target is known to one of the agents.

A. *VisualizeEnvironment*

B. *Coordinated*

C. *VirtualTarget*

The above three steps are same as VLRTA* algorithm [1]. The following extension are made to the VLRTA* algorithm.

D. *CoordinateTargetInformation*

Once the target is known to one of the agent's, it will coordinate target information to the environmental agent.

E. *CalculateSearchArea*

As environmental agent has global view of the search space, it will calculate the search area and coordinate the search area as well as target information to each agent.

F. *AdjustVisionAngle*

Each agent will calculate the vision angle based on the target information and will focus the vision on the target. As the target is moving each agent will adjust its vision angle and coordinate the target information with each other using the environmental agent.

G. *RunMTSAlgo*

While moving towards the target each agent will exceute moving target search algorithm to capture the target when the target state is known to any one of the agent. If the target is in the vision of any agent, every other agent will get the target information as a result of coordination mechanism.

IV. VMTS Framework

Our proposed simulated test system is very dynamic in nature. User has the option to specify the followings.

A. *Maze Size*

Initial size of the maze, the increment in the size and the final size.

B. *Number of Agents*

Initial number of agents engaged in the search, increment in each run and the maximum number of agents.

C. *Obstacle Ratio*

Initial Obstacle ratio, increment and maximum obstacle ratio.

D. *No of Different Mazes*

User can specify how many different random mazes for each obstacle ratio will be generated.

E. *No of Trials*

The number of trails to be run for each maze

In our framework, agents, obstacle positions and target position is randomly generated. For each run the agent(s), obstacle(s) and target position are different where as for each trail the positions remain the same. Agent(s) cannot predict target position nor can use any probabilistic function to locate the target position i.e. they have to search the space to locate the target. Agents can move in eight directions including the diagonals. Each agent has an infinite vision and its vision can be blocked only by obstacles in the search space. Agents coordinate their vision with environmental agent who has global view of the search space. For simplicity, we have assumed that all edges in the maze have unit cost. The goal of the agents is to cooperatively attempt to locate and capture the goal state in various random scenarios.

We have generated mazes of different sizes ranging from 10x10 to 100x100 with an increment of 20. For each size we have generated mazes with obstacle ratio ranging from 0 to 50 percent with an increment of 10 percent. For each obstacle ratio, twenty different mazes were generated and for each maze 10 trails are run. For each twenty different mazes the number of agent's engaged in the search are changed from 2 to 9.

We have conducted more than 6000 test runs with different maze sizes, obstacle ratios and varied number of agents. The results produced during simulation demonstrates that VMTS is effective in both locate target time and solution quality.

1. Modeling of Agents

In our framework, agents have omni direction vision like human and can see in one direction at a time. Agent(s) vision can only be blocked by the obstacles in the search space. Since agent can see in one direction at a time, it will visualize its surrounding using the vision angle specified by the user. On the current state agent will completely visualize its surrounding in anti-clockwise fashion. After visualizing one direction it will change direction and view in other direction and continue doing it until it covers complete 360 degree or the target state is visible.

After completing the visualization step, agent will update the global structure by coordinating its vision with the environmental agent. If the target state is unknown after the visualization step, agent will request environmental agent for a virtual target. As environmental agent has global view of the search space it will generate a virtual target which will be in the unknown space. Agent will run LRTA* algorithm to reach virtual target and while moving it will visualize its surrounding and coordinate the information with the environmental agent until the virtual target is reached. The above steps are repeated until the target state is known to one of the agents. Once the target position is known to one or more agents they will coordinate the information with other agents using the environmental agent.

Each agent will calculate the vision angle based on the target information and will focus the vision on the target. As the target is moving each agent will adjust its vision angle and coordinate the target information with each other. While moving towards the target each agent will execute moving target search algorithm to capture the target.

2. Simulation and Discussion

In the following figures red flag is the target, blue shapes are the agents, yellow color shows the obstacles, green flag are virtual targets, black color shows unknown territory and white color shows known territory. In step 1 agent(s) position, target position and obstacle positions are randomly defined in search space as shown in Fig. 1.

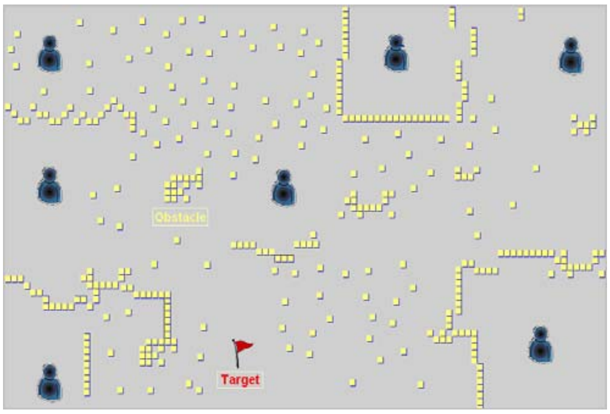

Fig. 1 Initial state of the search space with randomly defined obstacles, agents and target position

In step 2 each agent will start visualizing its surroundings using the vision angle which is taken as 45^o. As shown in figure 2 each agent starts visualizing its surrounding in anti-clockwise direction. White color arc's above the agent show the territory which it has explored while visualizing its surroundings. While these agent's are performing the visualization step, target has also moved from its original location as shown in Fig. 2.

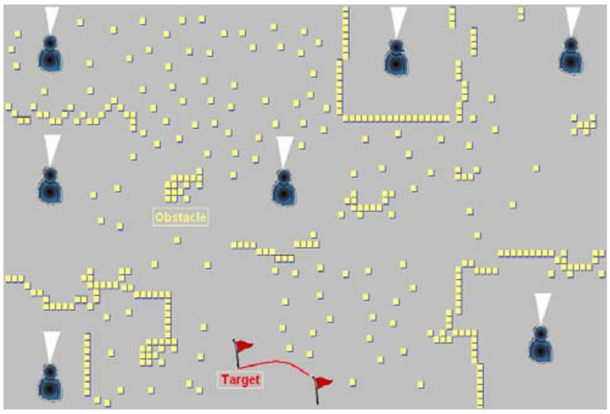

Fig. 2 Agent starts visualizing its surroundings

As each agent has omni directional vision, after completing one directional vision agent will explore the other direction and agent vision is blocked by the obstacles as shown in Fig. 3.

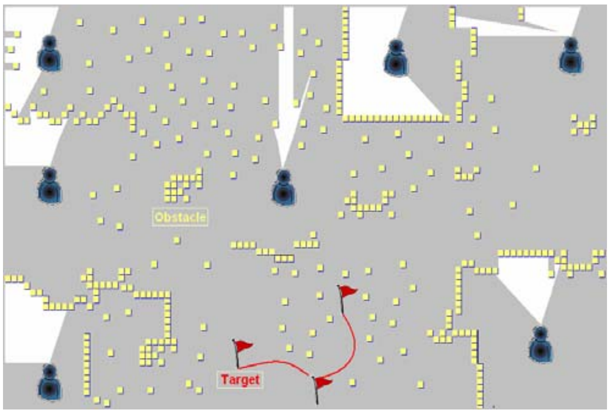

Fig. 3 Agents continue visualizing

As shown in Fig. 4, three agents have completed their omni directional vision and now they will update the global structure by coordinating their vision with the environmental agent and also request it to assign them new virtual target.

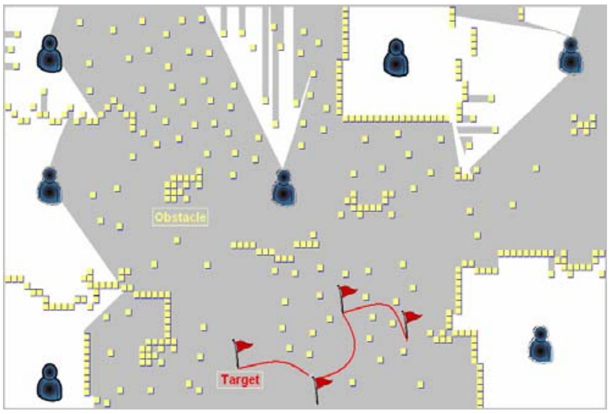

Fig. 4 Three Agents have completed their 360 degree vision

Environmental agent will create three distinct virtual targets and assign these to the requesting agents as shown in Fig. 5.

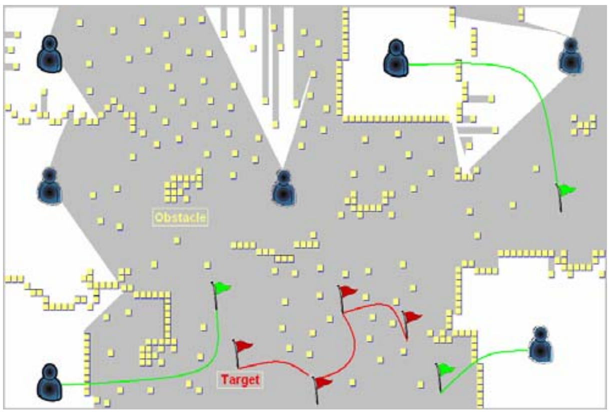

Fig. 5 Agents are assigned virtual targets

The agents who are assigned the new virtual targets will execute MTS algorithm to reach them and during their moves they continue visualizing their surrounding and coordinate their vision. The unknown vision of Fig.5 has now been explored and target status has been made known, even before reaching the virtual target as shown in Fig. 6. One of the agents has seen the target because it has come in its vision range.

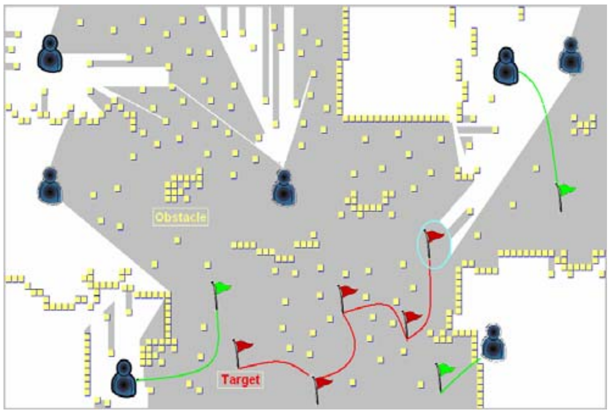

Fig. 6 Target is located by one of the Agent's.

Once the target is known, the target information will be coordinated to each agent. Every agent will adjust its vision angle according to the target position and will focus on the target as shown in Fig. 7.

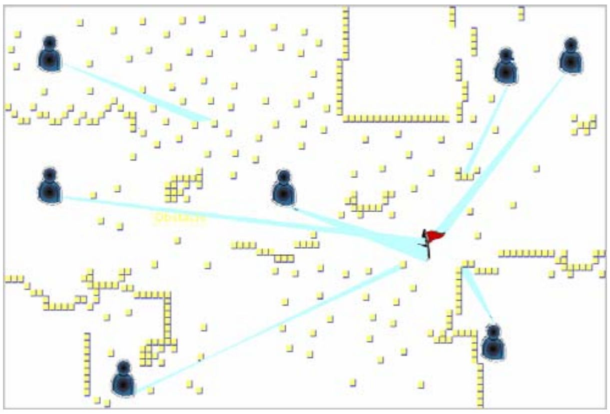

Fig. 7 Agents adjust their vision angle with reference to target

Each agent will change its vision angle according to the target movement and will end its vision when the target state is reached by one of the agents as shown in Fig. 8.

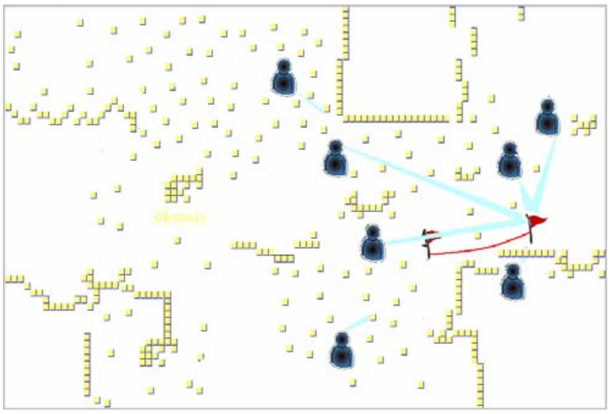

Fig. 8 Narrowing the distance between agents and target

V. Performance Analysis

Performance of VMTS was tested using grids of sizes ranging from 10x10 to 100x100. Grids had obstacles randomly placed, occupying 0% to 50%, in increments of 10%, of the space. The experiments used 2 to 9 agents. Agents positions as well as target position is different for each run where as for each trails these configurations remains the same. For each obstacle ratio we have generated thirty different mazes with random obstacle positions. For each maze twenty trials were run then the average of these trials was taken. Average of these thirty mazes is generated against same obstacle position.

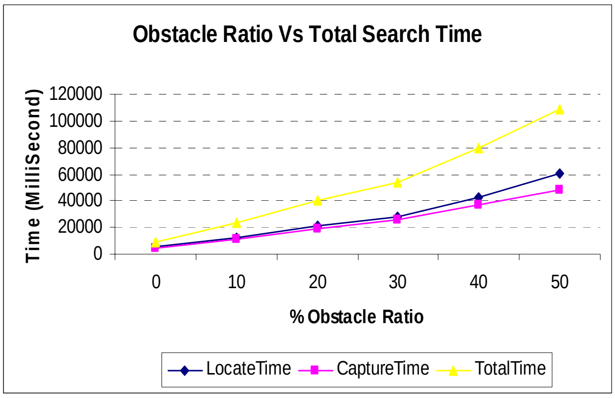

Fig. 9 Obstacle Ratio Vs Total Search Time

Fig. 9 shows that agent's take less time in locating the target when the obstacle ratio is less. As we keep on increasing the obstacles agent vision will be blocked and less search space will be explored so more virtual targets will be made as shown in Fig. 10 and more time will be required to locate the target.

Fig. 10 shows a comparison between the No of agents and number of virtual targets required to locate a target on obstacle ratio ranging from 0% to 50%. As we increase the number of agents with respect to obstacle ratio, VMTS efficiency increases.

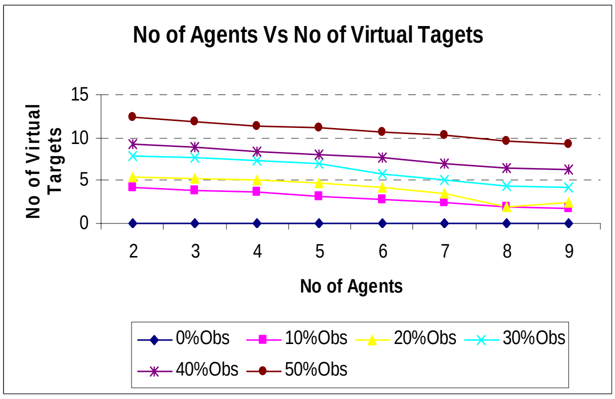

Fig. 10 No of Agents Vs No of Virtual Target

Fig. 11 shows that higher the number of agents better would be results. As the number of agent increases, search space to be explored by each agent decreases as a result less time, solution length it will take to locate and capture the target as shown in Fig. 12.

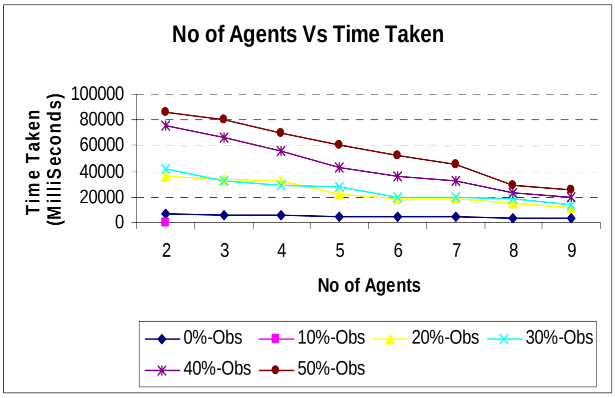

Fig. 11 No of Agents Vs Time Taken

Fig. 12 shows that as we increase the obstacle ratio in the mazes, search space becomes more congested and narrowed with obstacles; it gets harder for the agents to find the target. Essentially, a higher percent of obstacles provide the target more opportunities to hide.

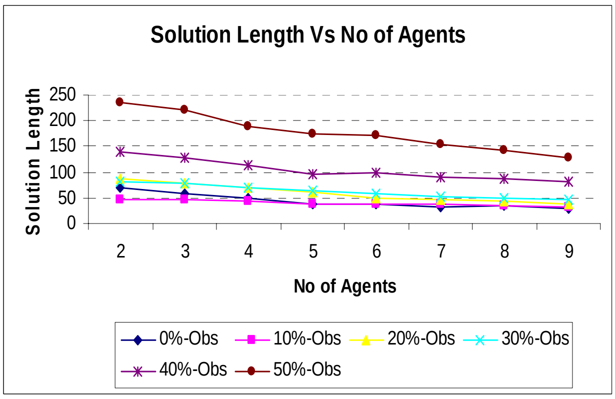

Fig. 12 Solution Length Vs No of Agents

At obstacle ratio 0 percent, increasing the number of agents has very less effect on efficiency of proposed solution because agent vision will not be blocked and even few agents can find and capture the target in the same time. But as we keep on increasing the obstacles agent vision will be block by these obstacles so the number of agents engaged in the search will have more effect on the search time as well as solution length. After 30 percent obstacle ratio, number of agents plays an important role because of hurdles in the path. As shown in Fig. 12, nine agents engaged in the search will take very less moves than two agents engaged in the search because each agent will be following a distinct path towards the goal state so more chances of getting the target in less time and less moves.

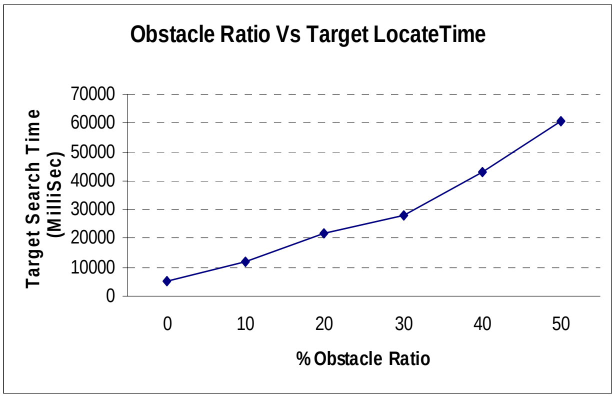

Fig. 13 Obstacle Ratio Vs Locate Time

Fig. 13 shows that agents take less time to locate the target when the obstacle ratio is less. Obviously, as we keep on increasing the obstacles in the search space agent vision will be block by these and less search space will be explored so more time will be required to locate the target.

In Fig. 13, 14, 15 the number of agents engaged in the search are taken as constant (five) and thirty different mazes are generated for obstacle ratio ranging from 0-50 with an increment of 10 percent. We have used the average value for these thirty mazes for generating the graphs.

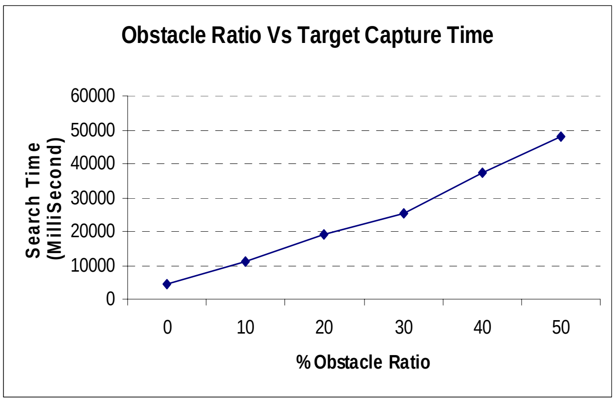

Fig. 14 Obstacle Ratio Vs Capture Time

Fig. 14 depicts the same pattern as Fig. 13. As the number of obstacles is increased, agent's minimal path will be blocked and agents may have to take the longer path to capture the target.

Fig. 15 shows that if the agents vision is blocked by the obstacle and target location is not found then these agent's will make more virtual targets to explore the unknown territory; hence increase in the obstacle ratio leads to increase in the number of virtual targets.

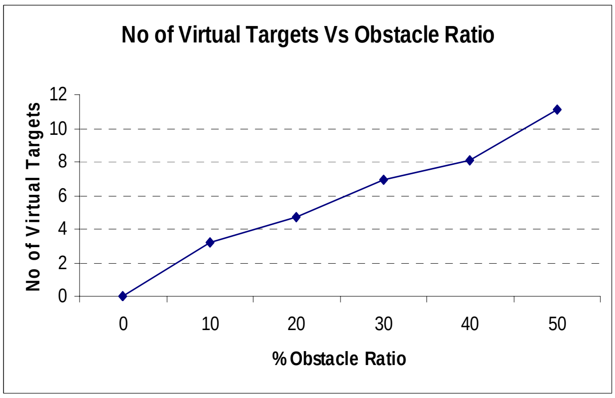

Fig. 15 No of Virtual Targets Vs Obstacle Ratio

VI. CONCLUSION

This paper proposed an extension to VLRTA* Algorithm known as VMTS which works for unknown moving target in unknown territory. Agent have human like vision but can see in one direction at some point in time. We have shown that our proposed scheme efficiently locate the target position because of the coordinated vision and virtual targets. Experimentally we have shown that VMTS is effective in both locate target time, solution quality and virtual target.

The current framework has many opportunities for further extensions. It can be applied for intelligent target or human like target behavior. Other possible extension would be to implement it in 3D space and also incorporate it with GIS for Missile systems to locate & hit moving target. Better Coordination Scheme can be developed for coordinating vision among agents. Optimized Scheme for creation of virtual targets can be devised.

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