Instituto Superior Técnico

Autonomous Agents and Multi-Agent Systems

UAV-based surveillance system for fire prevention

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Abstract

The project presents an Unmanned Aerial Vehicles (UAVs), consisting of many aerial vehicles for fire watching. Fire watching is outlined as the computation in period of time of the evolution of the fireplace form regarding different parameters associated with propagation. The project shows how an UAVs will mechanically get this information. Moreover, it is shown how multiple aerial vehicles will collaborate during this application, permitting to cover larger areas or to get complementary views of a fire.

1 Introduction

Forest fires represent a continuing threat to ecological systems, infrastructure, and human lives. An effective way to minimize the harm caused by forest fires in their early detection and quick reaction. Efforts have been made to attain early fire detection, that is historically supported by human investigation. There are two types of human investigation – direct human observation by observers situated on observation spots and distant human observation supported video investigation of the systems. These estimations are, nevertheless, subject to a large range of errors due to smoke occluding the flames, human inaccuracy within the visual estimation and errors within the localization of the fire. Because of these problems, a more advanced approach has been applied such as the automatic surveillance and automatic early forest fire detection – UAVs.

In this project, UAVs for automatic real-time forest fire monitoring and measurement is presented. The extension of a forest fire can be very large, so the system can integrate information from several aerial vehicles, that can collaborate to cover the fire from complementary points of view. The system is able to provide the current position of the fire front in geographical coordinates.

2 Problem statement

Wildfire simulation has attracted important analysis over the past decades, thanks to the potential in predicting wildfire spreading. The core model of existing wildfire simulation systems is the fire spreading propagation. However, in order to implement the model, we need to know data concerning fuels, earth geography, weather, conditions of terrain, and topography. To specialize in the scope of multi-UAV management instead of following a correct fire growth model, during this project we modify the fire spreading propagation model to describe the fire fronts growth in a simplified model. We also make the following assumptions:

- the model will be implemented for a discrete grid-based environment;
- the steady-state rate of spreading is already calculated using random methods (shown in section 3.3);
- every grid points spread;

Figure 1 shows the forest fire monitoring scenario considered in this project. The orange and red in pixels represent the areas where fire risk is high, while the black in pixels (not visible yet) represents the area that is starting to burn. Green pixels represents safe area.

Figure 2 shows the forest fires observations. The black outline represents the field of view of each UAV and figure 3 Current last time visited state shared between the UAVs.

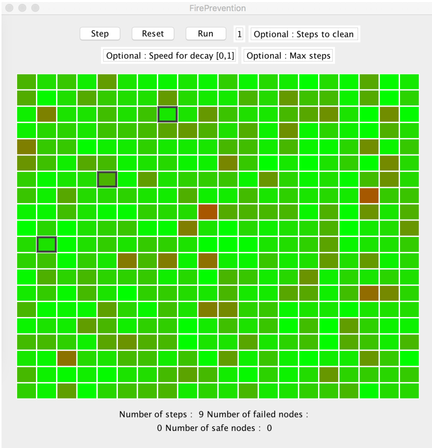

Figure 1: Fire monitoring scenario

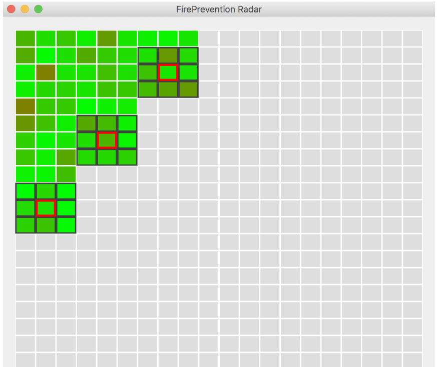

Figure 2: Current internal state

Figure 3: Current last time visited state

3 Unmanned Aircraft System for fire monitoring

The UAVs described in this paper is composed of a team of aerial vehicles. This section summarizes the requirements at the level of the whole system.

3.1 Perception system description

- *Wall-Right?* - Checks if there's a wall to the agent right.
- *Wall-Left?* - Checks if there's a wall to the agent left.
- *Wall-Up?* - Checks if there's a wall above the agent.
- *Wall-Down?* - Checks if there's a wall below the agent.
- *Object-Right?* - Checks if there's another agent to the right.
- *Object-Left?* - Checks if there's another agent to the left.
- *Object-Up?* - Checks if there's another agent in the tile above.
- *Object-Down?* - Checks if there's another agent in the tile below.
- *IsProtecting?* - Checks if the agent is currently protecting a risk area.
- *LocationRisk?* - Checks what's the risk of fire of the agent current field of view.

3.2 Actuation system description

- *Protect* - When the agent finds a location with high risk he starts protecting the area.
- *Protecting* - Responsible for lowering the fire risk of an area that has been selected for protection.
- *SetLocation* - Updates the shared view state of the UAVs with the agent's current field of view.
- *MoveRandom* - Moves the agent in a random direction.
- *MoveUtilityBased* - Moves the agent according to an utility function.

3.3 Decision-making system

An expected utility function was developed to perform risk analysis supported by the probability and severity of doable occurrences, that is based on results from random simulations that establish totally different failure modes throughout operations.

3.3.1 Reduced State Space

The set of all possible states includes every position the drone could be in. States are parameterized by the n-tuple S{X, Y, B, D} where X, Y refers to position coordinates $\{1 \leq X, Y \leq N\}$, B is whether the drone is out of bounds, and D is whether the simulation is done.

3.3.2 Actions

There are 4 possible actions, involving motion or observation taking: up, down, left, right and look. In a non-stochastic world, up action moves the drone in the positive Y direction, right moves in the positive X direction. Look does not move the current location. Instead, makes an observation through a sensor reading.

3.3.3 Observations

Our observations are simply represented as a integer value representing whether or not the object can be seen in the frame. The drone can see one square (its current square) and the surrounded squares from each direction.

3.3.4 Belief

We consider the system where the reward is known and the position of the drone is not. As time progresses, the belief of the drone's current state moves with the perceived action taken, and is strengthened or weakened by the presence of positive or negative observations.

3.3.5 Transition Function

When the drone attempts to execute an action, with the exception of look, it is possible that it executes a different action. We let the probability that the drone executes the correct action be P. Mathematically, if the probability of being in a certain state S{X,Y,B,D} is P(s), the new probability after transitioning with action A is $P_{new}(s_0) = \sum_{I=X-1}^{X+1} \sum_{J=Y-1}^{Y+1} \sum_{B=0}^{1} P(S\{I, J, B, 0\}) \times (s_0|s, a)$, where T is the probability of transitioning to state so after taking action a in state s.

3.3.6 Reward Function and Discount Factor

Every time the drone attempts to move out of bounds it gets a reward of R = 0. Transitioning to a fire risk cell has a reward R = 10. Every time the drone executes an action due to an unknown cell (cell not discover yet) it gets a reward R = 4 and it gets a reward R = 1.3 every time the drone ends up in a older cell – the number of time steps passed without being seen. The last reward helps the UAVs to have a complete coverage of the board, since the region is divided among the available UAVs accordingly with their field of view.

4 Simulations

Our simulation was conducted in a Java environment. We started with 1 UAVs from a initial position located in the left corner of the board. The UAVs were equipped with a camera capable of capturing 6 squares from the current position from every direction. We collected data on safe nodes and failed nodes while incrementing the number of UAVs till we experienced 0 failed nodes. We ran simulations in Java for 10000 time steps which yielded the results shown in the figures below.

We noted that if we increase the number of UAVs the number of failed nodes decline at a constant pace (figures 4-6). The safe nodes also increase but this increase gets gradually smaller as the total size of the board rises as seen in figure 8 and 9. After running the tests we concluded that each drone could protect 100+-2 squares (figure 7) . We also think that if a number N of agents can protect a certain area and this N is minimal while also ensuring 0 failed nodes, then there's no need to go above that because the gain in safe nodes and consequentially lower medium fire risk is not that noticeable.

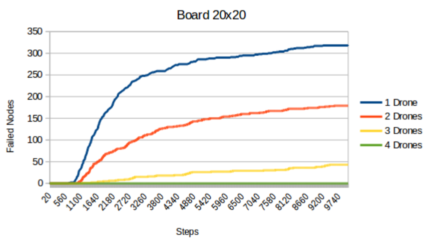

Figure 4: Failed nodes on a 20x20 Board

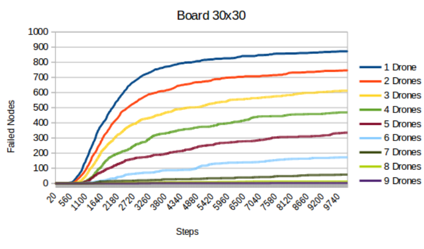

Figure 5: Failed nodes on a 30x30 Board

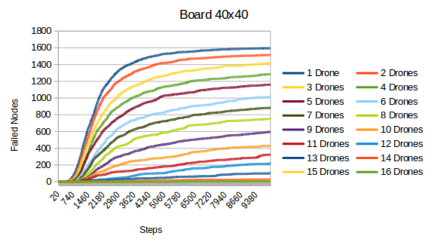

Figure 6: Failed nodes on a 40x40 Board

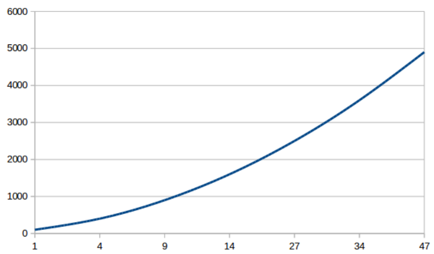

Figure 7: Variation of drones per meter

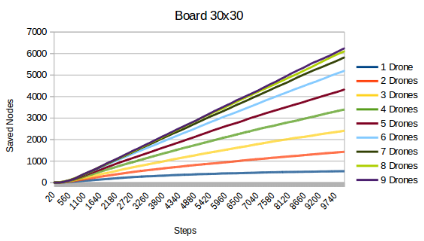

Figure 8: Saved nodes on a 30x30 Board

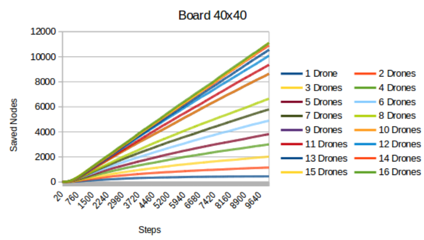

Figure 9: Saved nodes on a 40x40 Board

5 Conclusion and future work

This project has given a perception system for fire monitoring using UAS. The system integrates the knowledge from the fleet of several vehicles to get an estimation in real time of the evolution of the fire.

The UAVs are capable of avoiding collision, and flexible in deployment as shown in section 4. They can also follow the most critical areas of the wildfire as it keeps increasing, whereas still attempt to maintain coverage of the full wildfire.

The project could actually go beyond the scope of wildfire propagation, as it can be applied to any dynamic setting, for example, oil spilling or water flooding. In the future, a lot of work should be thought-about to this analysis. For instance, we should pay attention to the communication between the UAVs below the condition of a regularly ever-changing topology of the networks, or the sensing endurance problem in the hazardous environment. Also, we would prefer to investigate the relation between the speed of the UAVs and the spreading rate of the wildfire and commit to synchronize it.

References

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[7] Github repository of our work: `https://github.com/Yommere/AASMA`