Smart Rescue Drones to Find Snowslide Victims

Raul S. Silva[1], **Márjory Da Costa-Abreu**[1]

[1]Departamento de Informática e Matemática Aplicada – Universidade Federal do Rio Grande do Norte (UFRN)
Caixa Postal 1524 – 59078-970 – Natal – RN – Brazil

raul95@gmail.com, marjory@dimap.ufrn.br

Abstract. *In the approach of using autonomous robots to find victims on risk zones, there are specific ones that can reach the victims faster, the Unmanned Autonomous Vehicles (UAVs), better known as Drones. For this to happen, artificial intelligence algorithms were designed to teach them to search for the victims faster. On this paper, a simulation of three drones flying on different environments was made based on a Hidden Markov Models with K-NN classifier as an artificial intelligence approach for the learning. The results revealed that for some environments, based on memory to store the paths and the classification of the objects, different hardware settings for the drones can be needed.*

1. Introduction

There are several autonomous robots that were made to help people. These robots can be used for entertainment, domestic activities, health care, military activities and so on. Robots like Cozmo [Coz] and the Vacuum Cleaners [VCl] are the most common and they use learning algorithms to do their jobs. However, these algorithms are less powerful than the ones that are used on other robots, like Atlas [Atl], the humanoid robot from Boston Dynamics company. This robot uses image processing to identify QR Codes, recognise paths and objects dodging obstacles and picking up objects.

There are also robots, like Unmanned Autonomous Vehicles (UAVs) or drones, that can save people or identify risking situations at the work environment. These drones are used to fly over the risk zones, such as mines and mountains with landslide or snowslide risk. Also, using cameras and sensors, they can search for survivors [Verykokou et al. 2016].

Based on that context, this paper propose a software simulation of three drones trying to find a specific object on a map with obstacles. Each drone needs to explore distinct ways to recognize the map. When a drone finds out the location of the aim, the others will be notified where the aim is, and based on the current recognized map, they will try to find the best way to reach the aim.

2. Related Work

There are a lot of proposals for robots, most of them are drones, that are used to move over a place and recognize objects. At this section, is present an overview about different proposals that are related to this work.

On [Cong and Ponnambalam 2009] was proposed an solution to the Mobile Robot Path Planning (MRPP) problem, using an Ant Colony algorithm. The researchers evaluated the algorithm on seven distinct maps, that was a grid with equal number of rows and columns. Each map had obstacles on some cells and the ant simulates the robot. The algorithm was executed 10 times for each map and resulted on 5 maps that had a shorter tour distance than a genetic algorithm.

On context of drones, [Verykokou et al. 2016] describes a solution to modeling a 3D version of disaster scenes with destroyed buildings to help the rescue teams on identification of possible areas that might have trapped people.

On [Araújo et al. 2017], the drones, using two cameras to take photos of a scene and solve the Visual Simultaneous Localization and Mapping (SLAM) problem. They propose a new identification method, the Air-SSLAM, and had compared it with two others, the BestOf2NearestMatcher and the FlannBasedMatcher. The results showed that even with the increase of the keypoints on image, the Air-SSLAM can solve the problem on a half of the time when compared with the other methods.

In [Shi et al. 2016], the aim was to identify illegal Drones on a security-sensitive area. It is a military application that uses Hidden Markov Models [Rabiner and Juang 1986] to identify objects with different spectrograms of sounds and find the drones.

Based on these works, this paper describes a simulated solution to find victims on a snowslide environment. The data set used to simulate the maps were based on [Cong and Ponnambalam 2009] data set. However, the present simulation uses three agents and a Hidden Markov Model as an artificial intelligence technique for the drone's flight. As well as [Shi et al. 2016], the agents are trying to look for specific features on the map to identify the objects and classify them. However, the features are not the different sound on spectograms, they are intervals of integers that simulates features like dimensions of the objects.

3. Proposed Methodology

3.1. Maps

The maps designed to execute the experiments uses grids of 15x15 cells to simulate a small environment and in a short time. For this work, the agents were three drones.

On the first scenario there are three drones (A, B and C) that are trying to find the aimed object, presented as a star symbol (*), without other objects dispersed on the map. For the second scenario, the drones are also trying to find the same target. However, there are other objects dispersed on the map and the drones do not have knowledge about these objects. When a drone finds one of these objects, a classification is made for it, then the other drones will be notified. They will learn about that and store the information on their memories.

3.2. Hidden Markov Model

These drones only know that they need to avoid the walls and what is the aimed object that they are searching for. However, they do not have any information about the environment, the objects and where they are located. In other words, the map is hidden from the drones and they need to search for the objects, while learning about the environment. Based on that, the Hidden Markov Model was used as a tool for an artificial intelligence algorithm to help the drones on their search.

The initial distribution is defined as the probability of how reachable a cell is by a drone, based on the cell's content. If a drone had flown over it, the probability is proportional to the time of the stored information about that cell on their memories. The transitions have probabilities to define a better path for the drones. When a drone is trying to fly from a cell to another, there is a conditional probability that helps on the decision if is a good choice for the drone fly on this way, depending on the current cell and the drones memories, that are volatile and shared between the drones. For the emissions probabilities, the drones will try to analyze if there is an object on a cell, depending on the current cell. It is also a conditional probability that helps the drones to chose good cells that is possible to have the aim object.

The transitions probabilities are calculated for 5 cells ahead on the four directions (up, down, left and right), assuming that the drone's camera can reach up to 5 cells on the four directions.

For the strange objects, the drones, the empty cells, the target and the walls, there is a feature to distinguish them. This feature is an integer interval to characterize the object found. When a drone discovers a cell that was not identified, a K-NN classifier is executed to learn about that cell, and define it as a strange object, drone, empty cell, wall, or if it is the aimed object the the drones are looking for. The K value chosen to select the nearest features is $K = 50$. At the experiments, a feature can range from 1 to 50. A feature for each class of objects is a number that belongs to a section of 10 integers on this interval of 50 integers. Therefore, the K value helps the classifier, using an euclidean distance, to chose the class that the found cell is more similar.

For the number of interactions, the experiments was executed over 100, 200 and 300 interactions for each instance of map. The time for the drone to forget the visited cells, was defined as over 5, 10 and 15 interactions.

4. Experiments Results

The experiments were executed 30 times for each map of each scenario with the distinct combinations of the parameters (e.g. number of interactions and drone's short memory time). After these 30 executions, the accuracy was calculated based on the samples where the target was classified rightly. The equation used for the accuracy was $\frac{a*100}{n}$ where a is the number of right classifications of the target and n is the number of samples that the aim was found and classified. The table 1 describes the accuracy for each test case on the scenarios. The columns are labeled based on the number of the scenario and the map, for example, the S1M1 means that the results for the column refers to the Scenario 1 on Map 1. Lastly, the rows are labeled based on the maximum number of interactions and the the number of interaction of the drone memory, for example, in I100M5 the I100 means maximum of 100 interactions and M5 means 5 interactions to drone's memory.

The maps with more strange objects and walls got the best accuracy, that means that the environments with more objects to learn are the best to find the target. Also, when the time memory was increased, the drones are capable to explore a bigger area and reach the target faster.

In comparison with [Shi et al. 2016], the results of the simulation are not too similar. However, for [Shi et al. 2016], the classifier was based on the sounds of the

Table 1. Accuracy

	S1M1	S1M2	S1M3	S1M5	S1M6	S1M7	S2M1	S2M2	S2M3	S2M5	S2M6	S2M7
I100M5	0%	58.82%	66.6%	25%	0%	80%	0%	50%	96.6%	33.3%	66.6%	26.6%
I100M10	0%	46.15%	76.6%	24%	62.5%	53.84%	0%	42.85%	76.6%	39.13%	100%	50%
I100M15	33.33%	48.14%	86.6%	27.27%	50%	56.25%	0%	27.7%	63.3%	23.8%	0%	60.86%
I200M5	27.7%	40%	70%	38.46%	44.44%	31.25%	12.5%	56.25%	70%	37.93%	25%	50%
I200M10	52.38%	44.82%	76.6%	40.74%	55%	64%	25%	54.16%	80%	51.72%	50%	53.3%
I200M15	43.47%	27.58%	83.3%	37.03%	57.14%	46.15%	18.18%	46.15%	66.6%	62.06%	61.9%	64.28%
I300M5	43.47%	53.84%	76.6%	30.76%	62.5%	52.17%	40%	60%	53.33%	62.96%	46.66%	34.48%
I300M10	52.38%	39.28%	66.6%	41.37%	37.03%	40.74%	31.57%	58.62%	70%	46.6%	31.03%	51.72%
I300M15	60.86%	40%	73.3%	41.37%	46.42%	48.27%	15.38%	34.48%	76.6%	26.6%	33.33%	43.3%

drones, and for the simulation, was defined a small interval of integer to simulate the features.

5. Conclusion

In this approach of simulation, the present work evaluated the capacity of the drones on flying over an environment with obstacles and unknown objects to reach an aimed object. For the simulation, the environment and objects simulates a snowslide area with trees, rocks, snow and a victim as the aim object.

The study of the simulations showed that for some places with many obstacles, the drone can have a short memory to store the paths, however it needs a bigger memory to learn about them.

In the future, the function for the drones to reach the target faster when it is identified will be improved using Manhattan distance. Finally, using other choices of parameters would allow to obtain a better average of the maps to get a good solution.

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