Multiple Robot Path Planning Strategies for Bush Fire Fighting.

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Abstract

This paper addresses path planning strategies for multiple robots to cooperate to extinguish a many fronted bush fire where the need to deliver adequate water to each fire front and for each vehicle to carry a limited supply of water is taken into account, as is the time to extinguish each fire front, whose ferocity is proportional to the quantity of water required (estimated) to extinguish it. Both minimal total path length and minimal overall time solutions are sought. The number of robots available, their water carrying capacities and their speeds are specified, as is the number, locations and severity of fire fronts distributed over a known environment with obstacles.

1 Introduction

The potential for minimising the risk of death or injury as well as property loss provided by the fire fighting robots operating where human deployment is too dangerous is clearly worth investigating. In realistic situations, such robots would support the human agency in extinguishing the fires, subject to human judgement and operating with various degrees of autonomy as specified by responsible humans. However, it is still of value to study optimal and near optimal deployment strategies for multiple robots to extinguish a many fronted bush fire, since, at very least, this would provide an analysis basis upon which human/robot team combinations may act cooperatively, since the basic scenario assumptions would have direct relevance whether manned or unmanned fire fighting vehicles were involved.

The following assumptions are made concerning the situation to be analysed. Variation may be considered as extensions, some of these being considered in the discussion section.

1. A map showing all obstacles is provided.
2. The location and severity of each of many fire fronts are specified.
3. The number of robots (vehicles) and the speed and water carrying capacity of each is known.
4. The severity of each fire front, as indicated in (2), above, is directly proportional to the amount of water needed to extinguish it.
5. The time to extinguish each fire front is directly proportional to the quantity of water needed to extinguish it and this proportionality factor is specified.

Given the map showing free space, obstacles, fire fronts and robot locations, together with details of speed and water carrying capacity of each vehicle as well as the water quantity (and hence time) required to put out each fire front, the solutions sought are the allocation and paths to be followed by the robots to complete the fire fighting task in minimal time and, separately, for minimal total path length.

For simplicity, the refilling of robots with water is not considered, but a more realistic analysis could include the returning of a robot to refill depots before being again deployed for fire fighting.

From a computational geometry viewpoint, the problem is one of a multiple travelling salesman's type with constraints, for which there is no closed form known optimal time solution and thus a problem for which heuristic mechanism can be justified. The path lengths of all of the components of a solution are taken as distance transforms [Jarvis , 1993] (DT) path lengths which are shortest between points when obstacles are to be avoided.

The following section outlines the means by which the path length components are calculated and formulated into a simple data structure over which the search for optimality can be carried out. Then follows a section on the GA formulation of the problem. The next section presents some solution examples. Then follows a section on discussion and future work. A conclusions section completes the paper.

2 Multiple Distance Transform Path Lengths

There are p robots and q fire fronts and the location of each is specified in the environmental map, and is also empty and occupied (obstacle) cells. A matrix showing all the distances between these p and q identities is a good starting point for the analysis to follow. If we assume distance is reflective then a distance matrix of dimension (p+q) (p+q) would be symmetrical about its major diagonal which itself would be a string of zeros, each point being zero distance from itself. However, Euclidean distance (or cellular space approximated version) is not particularly useful because of the obstacle which need to be avoided. Thus we used Distance Transform (DT) distances instead, these properly providing the shortest navigable distances between point (cell) pairs. The DT is easy to calculate by propagating distances out from goals throughout connected free space, planning around the obstacles. Shortest paths to a nominated goal is provided by steepest descent through the DT flow field of distances. The evaluations are globally correct, no local entrapment being possible (as can be the case for potential field methods). Whilst multiple goals can be specified, the shortest path to the closest being sought in such a case, this is not what is required here. The (p+q)(p+q) matrix of distances referred to above is calculated as follows:

- For each robot and each fire front (representative) cell, p+q in all, generate the DT with only it set as the goal(zero distance from itself) so that all of connected free space has a route equal to the minimal number of steps required to reach it. For this evaluation, regard other robots as free cells (since they will most probably move) but all other fire front cells as obstacles. Put the step count value at the position of all robots and the step count values of the least value neighbouring free cell of fire front cells(which are themselves regarded as obstacles) into the appropriate rows and columns of the distance matrix.

The above evaluations need to be carried out precisely (p+q) times. Since the DT can be very efficiently evaluated this is not a severe computational burden.

In terms of the minimal total distance optimal solution search, every fire front cell must be allocated a robot so that the total distances covered by all the robots is minimal subject to the constraints of water carrying capacities and water required for extinguishment. Such a solution would provide a set of paths taken by the subset of robots (perhaps even all the robots) administering relief collectively to all the fire fronts, if such a solution exists. Adjustments to the number and capacities of the robots may be needed to find an acceptable solution.

The minimal time solution also provides a set of paths as in the previous case but now the completion time for the total extinguishment of all the fire fronts is to be minimised taking into consideration the water carrying capacities and water extinguishment requirements as well as the times for path navigation and fire front extinguishment. The total time that matters rather than the sum of all lengths of the paths taken by the robots.

The 'feed stock' for the search algorithm is the DT distance matrix, the speed and the water carrying capacities of each of the robots, plus the water extinguishment quantity and time for extinguishment(related) for each of the fire front cells.

The complexity of an exhaustive search is very high since each allocation of a set of fire fronts to a robot requires a travelling salesman like solution and visitation order but with constraints added. Returning to the start allocation is not needed.

3 Genetic Algorithm Solution Formulation

The approach taken by us to tackle this problem is a heuristic one similar to those for the Bin-Packing Problem:

- Assuming that there are n items with volumes $v_1, v_2, ..., v_n$ which are to be placed in m bins, $b_1, b_2, ..., b_m$, each with a capacity of C. The objective is to minimise the number of bins used. Initially, all m bins are empty. If the heuristic applied is Best Fit, then the first step is placing v_i in b_j, where the difference of volume $(b_j - v_i)$ is the maximum once i-th object is placed into the j-th bin. After the placement, the original problem is changed in both senses of available capacity and items waiting for placement. Then the Best Fit heuristic is re-applied repetitively until all items are placed.

Similarly, our Bush Fire Fighting Problem is to minimise the total length of paths taken, or the total time required, to put out all the fire fronts. What is required is a heuristic to decide which will be the next robot to be assigned to one of the fire fronts. The attributes based on which to make decisions are:

- The distance between i-th robot and j-th fire front. Originally, i=1..p, j=1..q.

- The requested travel time for i-th robot to arrive at j-th fire front
- The capacity of water left on i-th robot after putting out j-th fire front

A fire front that has not been assigned a robot is called an un-assigned front. Originally, all fronts are un-assigned. In a similar way for the Bin Packing Problem, once a robot is assigned, the original problem is changed in the senses of the reduced number of un-assigned fronts, the whereabouts of robots, capacity of water left, etc. The same heuristic will be applied to the new problem repetitively until all fire fronts are assigned.

The method used to generate a heuristic for the problem of this paper is a genetic algorithmic approach. Details of the GA are available from [Tang and Jarvis , 2005]. Some more necessary elaborations are given as follows:

For each un-assigned fire front, every robot will be evaluated to see which of the robot is the best servant to it based on the above three attributes, plus when the robot can arrive at the front. This fourth attribute is equal to the time when the robot has finished extinguishing its last assigned front plus the travel time. It has to emphasise that a robot may be the best servant for more than one fire front. This first round evaluation is called the preliminary assignment in which results are matched pairs of robots and fire front.

For the sake of completeness, we highlighted here that if refilling is necessary, then two more attributes have to be added to the list:

- The distance between i-th robot and k-th refilling station, assuming that there are r refilling stations, i.e. k=1..r.
- The requested travel time for i-th robot to arrive at the r-th refilling station

Then the result of the first round evaluation will be robot / refilling station as well as robot / fire front pairs. However, since the refilling of robots with water is not considered in this paper as mentioned before, these two attributes are excluded.

After the preliminary assignment, two attributes, one for the robots, and the other for the fronts, are added.

- Accessibility, attribute of a fire front, indicates how many robots are equipped with enough water to serve it.
- NumBestClients, attribute of a robot, indicates among the preliminary assignments, how many of them are associated with this robot.

A second evaluation will be used to choose which preliminary assignment is the next true assignment. This time, the quantities of: the path length, travel time, water left, accessibility of the fire front and NumBestClient of the robot are used to make the decision.

The decision-making processes of both evaluations are in the form of a decision tree (fig. 1).

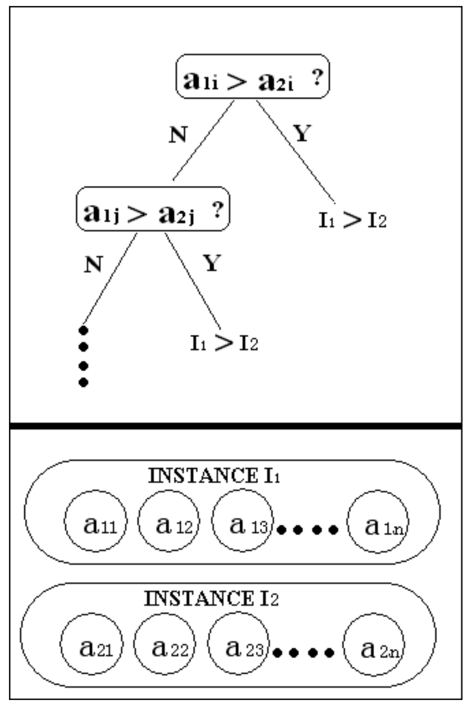

Figure 1: Decision Tree, a_{ij} is the attribute.

During an evaluation, following a pre-defined order, two instances are compared. If it is the preliminary assignment phase, then an instance is a robot. If it is the second phase, an instance is a robot-fire front pair. A set of margin of difference is used to determine if the comparisons of attributes are enough to draw a conclusion. If the result of the prior attribute comparison is equal, the next attribute will be compared until a distinction can be made. If all differences are within the ranges, then the two instances will be treated as equals.

The order of comparisons and the margins of difference are the phenotypic parameters for the GA to search:

The phenotype is composed of two portions, the first portion defines the order of significance and the second portion defines the margin of distinction.

Suppose there are n attributes, the first portion will consist of (n-1) genes and the second portion n genes, respectively.

For the first portion, the 1st, 2nd, 3rd, ... (n-1)th gene will have values within the range of {1..n}, {1..(n-1)}, {1..(n-2)}, ... {2}, respectively. This portion represents n! combinations of comparsion sequences of the n attributes.

For example, let n = 6. The first portion will consist of n-1, i.e. 5 genes. The value of the first gene is in the range of {1..6}, and the fifth is {1..2}, etc.

Let the six attributes are named as A, B, C, D, E, F. The value of the first gene defines the place of the most important attribute in this list. According, the value of second gene will be the place of the most important one in the list excluded the first one.

Let the values of the genes be: 5 1 3 2 1

The most important attribute is the fifth, i.e. E. Then E is remove from the list.

init: A B C D E F —-(5::E removed)
left: A B C D F ——-(1::A removed)
left: B C D F ———-(3::D removed)
left: B C F ————-(2::C removed)
left: B F —————-(1::B removed)
left: F

Therefore, the genes of values 5 1 3 2 1 defines the significance order of E A D C B F.

Basically, this is a form of Ordinal Representation of Grefenstette which has been reported [Grefenstette , 1985] that is not very effective in solving Travelling Salesman Problem (TSP). It is because of a major drawback: front parts before the cutoff point of a classical crossover operation are preserved, but back parts of the offsprings are disrupted in a random way. From our observation, influences of the attributes with lower significance orders seem dropping steeply and this representation works satisfactorily for the application of this paper.

The second portion defines the margin of distinction. When two attributes are compared, if the difference is less than or equal to that gene's value, the attributive comparison result is considered to be equal.

4 Example Results

The dimensions of the simulation environments used environments are 64 by 112 cells. One environment is used for evolution and two others are used for testing purpose. Their forms are as shown in figures 2 to 4.

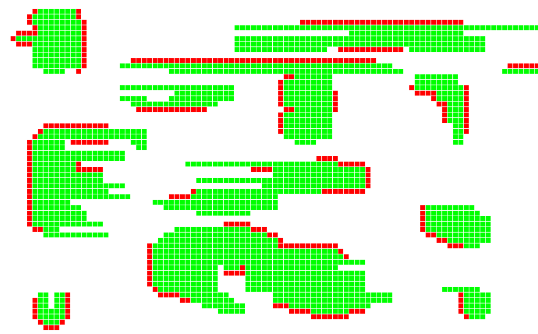

Figure 2: Evolution environment (green cells are bushes, red cells are fire fronts).

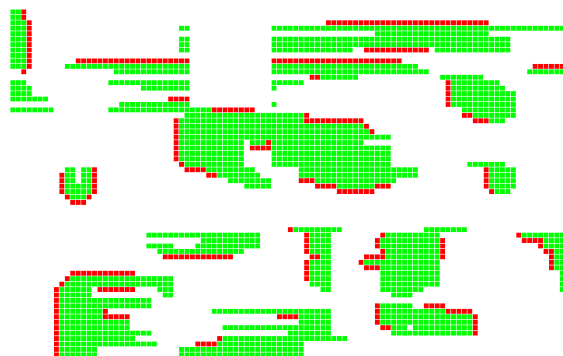

Figure 3: Testing environment 1.

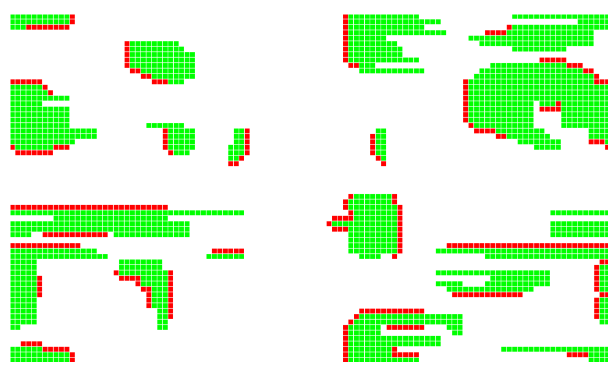

Figure 4: Testing environment 2.

There are three types of robots, the ratios of speed and water capacity for these three types are 1:2:3. That is, for a type-1 robot, its speed is three times as fast as; but its water capacity is 1/3 as a type-3 robot. During the evolution, five robots were used; two of them are type-1, one is type-2 and the others are type-3.

Just to further illustrate the result, one resulted heuristic is enumerated as follows:

During the first round evaluation (preliminary assginment of a robot to a fire front),

1. If the distance between robot A and a fire front is 3 units (or more) shorter than the distance between robot B and the same fire front, then robt A is perferred to robot B.
2. If the distance difference is less than three units, then if the difference in water capacity is more than 10 units, then the robot with the more capacity is preferred.
3. If both the differences in distance and water capacity are less than 3 and 10, respectively, then either one of the two robots will be selected ransomly.

During the second round evaluation (confirmation of a robot / fire front assignment),

1. If for assignment A, its robot is the champion of m fire fronts and for assignment B, its robot is the champion of n fire fronts and $m < n + 10$, then assignment A is preferred.
2. Otherwise, the assignment whose robot can access less fire front is preferred.
3. Otherwise, the assignment with a shorter distance is preferred.
4. Otherwise, if the champion difference is less than 10 and there is not difference in accessibility and distance, then the assignment whose robot with a higher water capacity is preffered.

After the evolution is carried out and a set of best parameters adapted to the evolution environment is constructed, four or five robots are randomly placed in the above three environments for trial running. In order to test the robustness of the results, different combinations of robot types are used. For each environment, thirty trials are run. The performance is compared to the greedy heuristic, i.e. assigning the robot to the site where the fire can be extinguished in the earliest moment. It is found that the evolved heuristic outperforms the greedy heuristic for an average of 15.0length, respectively. It is observed that the difference in performance is more serious when initial positions of the robots are scattered further apart. Under these scenarios the greedy heuristic will haphazardly allocate the robot with a lower capacity to some huge fire front and dry up its supply. Consequently, in the later part of an operation, only two to three robots can operate and the trial will lose the advantage of a co-operation.

In order to further test whether the performance of the evolved parameters is highly reliant on the evolution environment, a further test was run:

Testing environment 1 was used as a new evolution environment and hence a new set of parameters were constructed. We called the parameters obtained from the original evolution environment and testing environment 1 as P0 and P1, respectively. Then another thirty trials were run on both environments by P0 and P1. We found that for the trial whose locations of robots were identical as the one used for the evolutions, then it could outperform the other for 11.3%; otherwise, the difference in performance was less than 5%. Sometimes P0 was better, sometimes P1 was better. We deduce that a set of evolved parameters will be optimally fitted to the combination of locations of fire fronts, size of fire, locations of robots, and types of robots etc. Once there are some differences in the combination, the performance will be sub-optimal. The results of this last test showed that variations in the combination will downgrade the performance to roughly 5%, but the performance can be maintained at that level, relatively insensitive to the degree of variations.

Environment	Combination of robots	Average	Std.
Evolution Env.	1-1-2-3-3	14.7%	10.5%
Testing Env. 1	1-2-2-3	12.5%	8.8%
Testing Env. 1	1-2-3-3	15.7%	6.5%
Testing Env. 2	1-1-2-3	13.6%	9.7%
Testing Env. 2	1-2-3-3	18.6%	6.3%

Table 1: Performance gained compared with greedy heuristic (optimality in time)

Environment	Combination of robots	Average	Std.
Evolution Env.	1-1-2-3-3	23.3%	10.2%
Testing Env. 1	1-2-2-3	23.7%	8.6%
Testing Env. 1	1-2-3-3	22.3%	8.5%
Testing Env. 2	1-1-2-3	26.6%	8.9%
Testing Env. 2	1-2-3-3	25.6%	9.2%

Table 2: Performance gained compared with greedy heuristic (optimality in total path length)

Figures 5 and 6 are the examples of trajectories of robots in testing environment 2 for optimality in path length and time, respectively. The darker tracks are the paths of robots with a lower speed and more water.

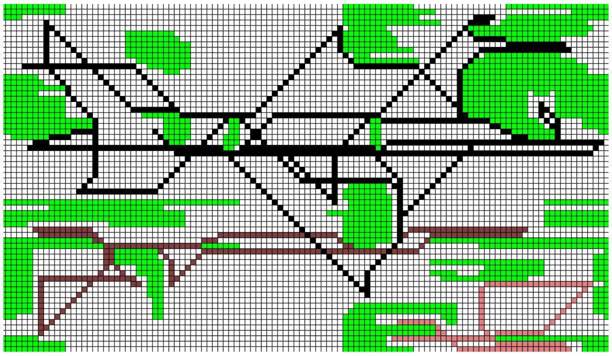

Figure 5: Trajectories of robots, optimal in path length.

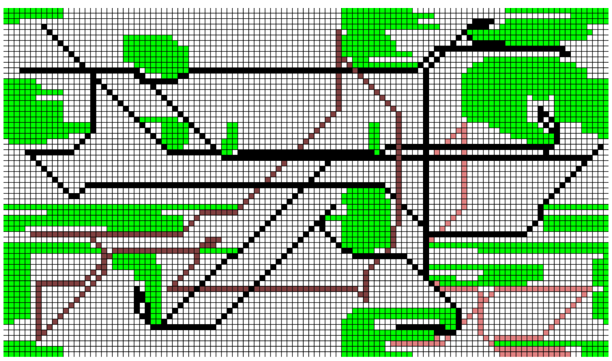

Figure 6: Trajectories of robots, optimal in time.

5 Discussion and Further Work

This paper illustrates an application of a Genetic Algorithmic approach to a complex resource allocation problem where complete and exact optimal solution would be prohibitively computationally expensive when the problem is scaled up. To date only relatively primitive aspects of fire fighting have been accommodated but the method should be able to accommodate factors relating to risks associated with approaching fire fronts and these in turn, may relate to ferocity as well as wind speed/direction in addition to anticipated weather changes. We have not considered the possibility of replanning in the face of a component failure nor the incorporation of uncertainty in a probabilistic way. Intuitively, it would seem that these considerations would have a high impact on the computational complexity of solutions and may prove intractable since the basic resource allocation problem is already difficult. The combinations and statistics of such extensions would likely be daunting. However, these aspects do seem worth pondering, both because of practical implications and the challenge to find ingenious solutions. Overall this paper represents just the beginning of possible useful outcomes of analysing realistic fire fighting problems using artificial intelligence methodologies which can produce a good, but perhaps not perfect, result in a timely manner for both robots and manual fire fighting vehicles.

6 Conclusion

This paper has presented an effective Genetic Algorithm approach to a complex resource allocation task involving multiple vehicles with varying speeds and water carrying capacity which need to be deployed over a multiple front bush fire scenarios. Examples illustrating the effectiveness of the approach and some brief coverage of possible future development are also presented.

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