Intro to AI Project 1

Tim Raymaker and Mike Rizzo

July 17, 2019

1 Part 1: Understanding the Methods

1a

The agent will move toward the cell with the lowest f-value. The f-value is determined from the sum of the cost from the start, or g-value, and the heuristic value to the goal, or h-value. For the first move, each possible direction is one tile away from the start, meaning that the g-value for each move will be the same, and differences in the h-value will be the deciding factor on where to move. Since the agent does not know that cells D3 and E4 are blocked, it will move to the east, the direction that leads to the cell with the lowest h-value and therefore the lowest f-value.

1b

The answer has been divided into four cases:

1. Case 1: In an infinite grid, the agent can find the target and the target is reachable. Yes, a path can be found in finite time.
   The agent will go about expanding reachable nodes that decrease in f-value over time. This will lead it closer and closer to the target until eventually it will encounter the target and stop. Assuming the target is not moving, it will be a finite distance away and therefore only a finite number of cells with generally decreasing f-values will be expanded between the agent and the target.

2. Case 2: In an infinite grid, The agent can tell there is no solution when the target is unreachable. A solution cannot be found; this case does not exist.
   The agent will expand all reachable nodes and even though the values of f will be generally decreasing, if the target is unreachable, the agent

will resort to cells with higher and higher f-values which in an infinite grid are also infinite and will thus never terminate.

3. Case 3: In a finite grid, the agent makes upper-bounded number of moves when the target is reachable. Yes, an upper-bound exists.
   Even in the worst case scenario where agent must expand every cell, there are only a finite number of them, so the number of moves will never exceed the size of the grid. In other words the number of moves will be less than or equal to the size of the grid.

4. Case 4: In a finite grid, the agent makes an upper-bounded number of moves when the target is unreachable. Unlike case 2, an upper-bound exists.
   It is in fact the same bound as case 3 and follows the same reasoning. Though the number of moves to find an unreachable cell does have a different lower bound. It will have to investigate every reachable cell in the finite grid before determining that the target is not in the finite grid.

2 Part 2: The Effects of Ties

Tie-breaking is important in the planning phase of the A* search. Favoring high g-values, in its attempt to 'greedily' find a solution as fast as possible, sometimes ended up trapped in dead end areas with no way forward, being forced to backtrack significantly. Favoring low g-values, on the other hand, performs a slower but safer search. In this way, favoring low g-values is akin to BFS while favoring high g-values is akin to DFS. Of course, the average and best case scenarios of Favoring high g-values are much better than those of Favoring low g-values.

In our implementation, tie-breaking in favor of low g-values meant prioritizing tied neighbors that were closer to the start in the heap. Tie-breaking in favor of high g-values meant the opposite. Overall, we observed for that favoring a high or low g in the case of a tie value had little actual effect on the performance of the Repeated Forward A* search. On average, the runtime for favoring low g was 5.84 seconds. Favoring high g was nearly identical, being slower on average only by a hundredth of a second at 5.86 seconds. Investigating further, we see the medians are still only fractions of a second in difference different with Though our runtimes were nearly identical, using g to tiebreak would likely be useful for performance on an empty map as it would help limit expansions. In the maps provided, the amount of obstacles in the way means that there is relatively little gain with manipulating g.

With more maps and more data, perhaps a higher density of average cases would have shown that tie-breaking in favor of high g-values will perform better overall.

3 Part 3: Forward vs. Backward

The Repeated Forward A* search and Repeated Backward A* search were both able to find possible solutions, where solutions existed, but their exact paths differed in most cases. The difference comes from the path planning and replanning. Because Repeated Backward A* plans from the goal, different blocked and unblocked cells are found at each iteration. Neither method's path was consistently superior to that of the other. This is likely because that although they solved the same maze, each one had different information available to them as they could only see cells near them. As such, their differing starting locations led them down different paths. Neither method's path was consistently superior to that of the other, but the backwards paths tended to have worse runtimes, perhaps due to the fact that we only animated the projected paths of A* in the first quadrant. Although the forward searches would have longer projected paths, the amount of replans for the backward searches was likely higher in the first quadrant as the searches neared their goal and the amount of available moves became more limited.

4 Part 4: Heuristics in the Adaptive A* (i)

The "Manhattan Distance" can be described as the number of moves required to reach a goal given no obstacles. Therefore, it makes sense that said distance will be consistent. If an h-value in adaptive A* becomes inconsistent, it is because something is in the way. In this case, the heuristic will be updated and will become consistent again.
Given a node s and neighbor m:

5 Part 5: Heuristics in the Adaptive A* (iI)

Our Adaptive A* method was able to find shorter paths than Repeat Forward A* on average, but it also took a longer time. This is likely due to it attempting to avoid previous projected paths and move in new directions. Our A* recalculated the heuristic value of every tile that was expanded by the previous A* search upon replanning, increasing their cost by using g(sgoal)-g(s) and incentivising the algorithm to explore alternatives. By doing so it was sometimes able to find a better path at the cost of runtime. Ties were broken randomly and each search weighed in favor of larger g values.

6 Part 6: Memory Issues

6a Improvements to Our Implementation

We currently use Python's tuples to record (x, y) coordinate information. According to Python's "sizeof" function, for one, 2-integer tuple, the memory consumption is 40 bytes. We could reduce this by storing the coordinates in the minimum number of bits it takes to store two integer values between $0 \rightarrow 100$. This would be 7 bits per value and 14 total. We could then also keep the tree pointers on two bits with 00, 01, 10, 11 corresponding to whether the neighbor is N, S, E, W of the current node. We can do this because the neighbors are only in discrete directions.

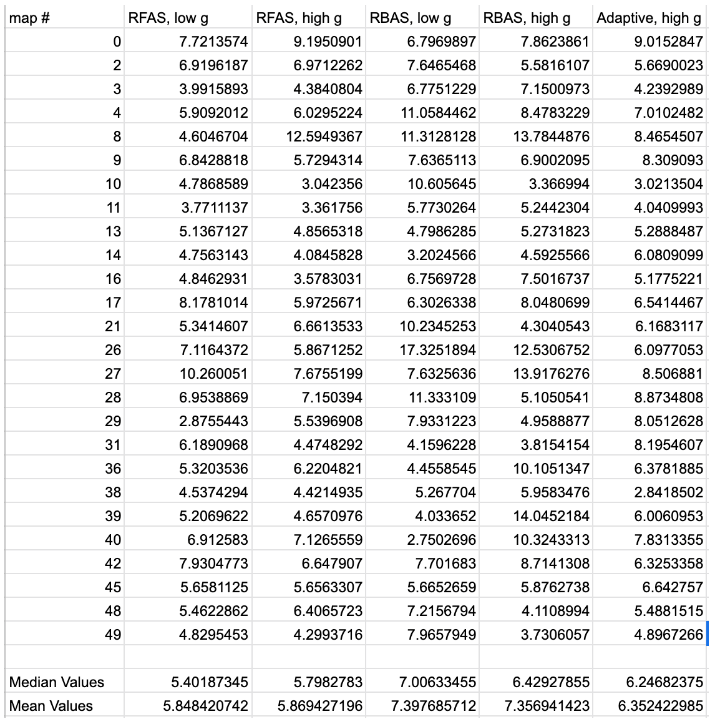
6b Calculations

(1,001 x 1,001) = 1002001 cells
At 2 bits per cell:
2 * 1002001 = 2,004,002 bits   250 kB

4MB = 32000000 bits
At 2 bits per cell:
16000000 cells possible
grid size = sqrt(16000000) = 4000 x 4000 grid

7 Data, Methods, and Observations

Data was collected for Repeat Forward A* with Tie-breaking in favor of Low g-values, Repeat Forward A* with Tie-breaking in favor of High g-values, Repeat Backward A* with Tie-breaking in favor of Low g-values, Repeat Backward A* with Tie-breaking in favor of High g-values, Adaptive A* with Tie-breaking in favor of High g-values algorithms. The searches were each performed on the 50 maps generated in Part 0. The start and end goal were standardized to $(0, 0)$ and $(100, 100)$. Of the 50, 26 had solutions. The 24 without solutions are marked in red and their runtimes are not included in the data because animation conflicted with reporting significant and comparable runtimes. For each of the 5 algorithms, we have calculated and provided a median and mean runtime. These values are recorded in the Figure 1:



map #	RFAS, low g	RFAS, high g	RBAS, low g	RBAS, high g	Adaptive, high g
0	7.7213574	9.1950901	6.7969897	7.8623861	9.0152847
2	6.9196187	6.9712262	7.6465468	5.5816107	5.6690023
3	3.9915893	4.3840804	6.7751229	7.1500973	4.2392989
4	5.9092012	6.0295224	11.0584462	8.4783229	7.0102482
8	4.6046704	12.5949367	11.3128128	13.7844876	8.4654507
9	6.8428818	5.7294314	7.6365113	6.9002095	8.309093
10	4.7868589	3.042356	10.605645	3.366994	3.0213504
11	3.7711137	3.361756	5.7730264	5.2442304	4.0409993
13	5.1367127	4.8565318	4.7986285	5.2731823	5.2888487
14	4.7563143	4.0845828	3.2024566	4.5925566	6.0809099
16	4.8462931	3.5783031	6.7569728	7.5016737	5.1775221
17	8.1781014	5.9725671	6.3026338	8.0480699	6.5414467
21	5.3414607	6.6613533	10.2345253	4.3040543	6.1683117
26	7.1164372	5.8671252	17.3251894	12.5306752	6.0977053
27	10.260051	7.6755199	7.6325636	13.9176276	8.506881
28	6.9538869	7.150394	11.333109	5.1050541	8.8734808
29	2.8755443	5.5396908	7.9331223	4.9588877	8.0512628
31	6.1890968	4.4748292	4.1596228	3.8154154	8.1954607
36	5.3203536	6.2204821	4.4558545	10.1051347	6.3781885
38	4.5374294	4.4214935	5.267704	5.9583476	2.8418502
39	5.2069622	4.6570976	4.033652	14.0452184	6.0060953
40	6.912583	7.1265559	2.7502696	10.3243313	7.8313355
42	7.9304773	6.647907	7.701683	8.7141308	6.3253358
45	5.6581125	5.6563307	5.6652659	5.8762738	6.642757
48	5.4622862	6.4065723	7.2156794	4.1108994	5.4881515
49	4.8295453	4.2993716	7.9657949	3.7306057	4.8967266
Median Values	5.40187345	5.7982783	7.00633455	6.42927855	6.24682375
Mean Values	5.848420742	5.869427196	7.397685712	7.356941423	6.352422985

Figure 1: Our Data

Sources of error can be attributed to small sample size and random choices in cases of g-values also tying. If there were more time, we would have like to address the small sample size by generating more graphs that tested specific edge cases as well as graphs at varying amounts of blockages. As well, the randomization in the implementation can lead to variance in the paths taken and nodes expanded even by the same search on the same map. Finally, optimization differences between different hardware and software may also have played a role in the uniformity of our data. We acknowledge these issues and have answered the as best as possible.