A Neural Network Case Base for Real-Time Searching

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(When I use "I" instead of "we", that means that part is my personal reflections and will changed in the final report.)

Abstract

Some real-time search algorithms use a case base to store previously solved problems and use the case base to build a new solution for an unknown problem in the real-time. Larger case bases leads to better performance at the cost of slower query time. In this paper, we build a neural network that is trained on the cases and achieve constant time for queries in any size case bases.

1 Introduction

Using a case base is common technique in real-time search algorithms. When an agent encounters a previously unknown task, it searches in its case base for similar situations, and infers a solution from the cases. As a case base covers more cases, an agent utilizing the case base will be more likely to find similar situations and solutions. However, the time cost of retrieving similar cases also goes up when the case base is larger. In this paper, we purpose Neural Network Case Base (NNCB), a case base that benefits from more cases, but does not suffer from the extra time cost.

Right now I have a few ideas of doing this.

- build a data base for inferring amount of heuristic updates
- build a data base for inferring actions
- build a data base for inferring an optimal path

2 Problem Formulation

We define a heuristic problem as a directed graph containing a finitely many number of *states*, in which one is the *start* and one is the *goal*, and *edges* connecting adjacent states with fixed costs of 1. The agent has a single *current state* at every time step. The agent can take an action by following an edge to change its current state. The *solution cost* is the sum of all edge costs of a path the agent can follow to go from the start state to the goal state. The algorithm has to be complete so it is comparable to the other algorithms.

3 Related Work

So far I have been comparing my algorithm with weighted LRTA* Bulitko & Lee (2006) Rivera, Baier, & Hern á ndez (2015). I implemented the neural network using pytorch by Paszke *et al.* (2019). One of the approaches I am going to try involve predicting the amount of learing and there's previous work on that by Lelis *et al.* (2012). I drew inspiration from Bulitko *et al.* (2007) Bulitko & Bj ö rnsson (2009) Lawrence & Bulitko (2010) for using a case base. I also drew inspiration from Mu ñ oz *et al.* (2018) on using a neural network on real-time search problems.

4 Proposed Approach

For this midterm report, most of my effort has been coding infrastructures (e.g, map/scene parsing, map/scene/path/heuristic-updates visualizations, agent-map interaction framework). See Figure 1 and Figure 2 for visualizations.

The first thing I tried is to build a case base to predict heuristic updates from a view and its distance to the goal.

Formally, for each entry in the case base, we have:

- $V_{i,j}$: a 7x7 matrix around the current state
- $d_{i,j}$: a 2D vector containing the difference between the goal and the current state
- $h_{i,j}$: the difference between the current state and the goal state

To use the case base, we start with a standard LRTA* procedure. When the agent wants to update a heuristic at given position i, j, instead of update the heuristic with a new f, the agent query the case base

Figure 1: LRTA Planned Path Visualized

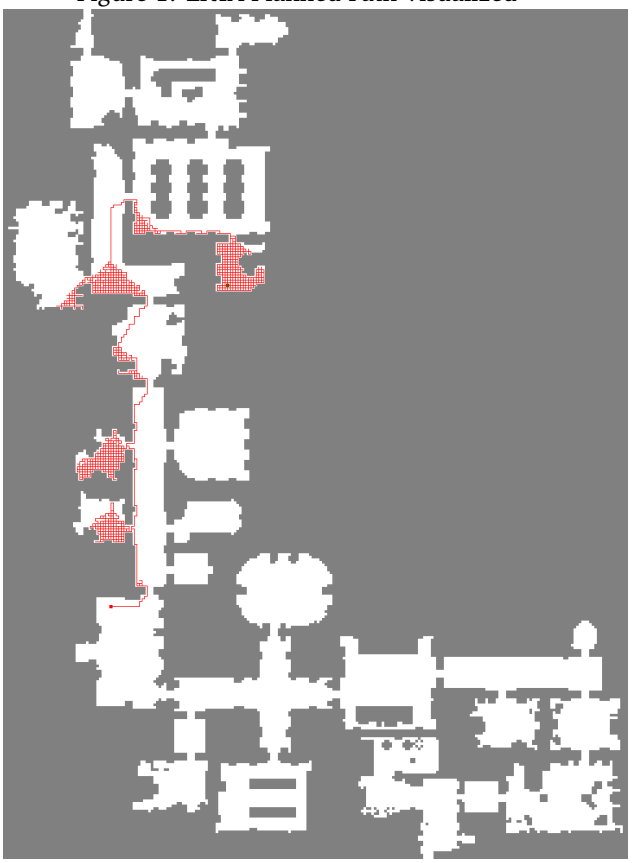
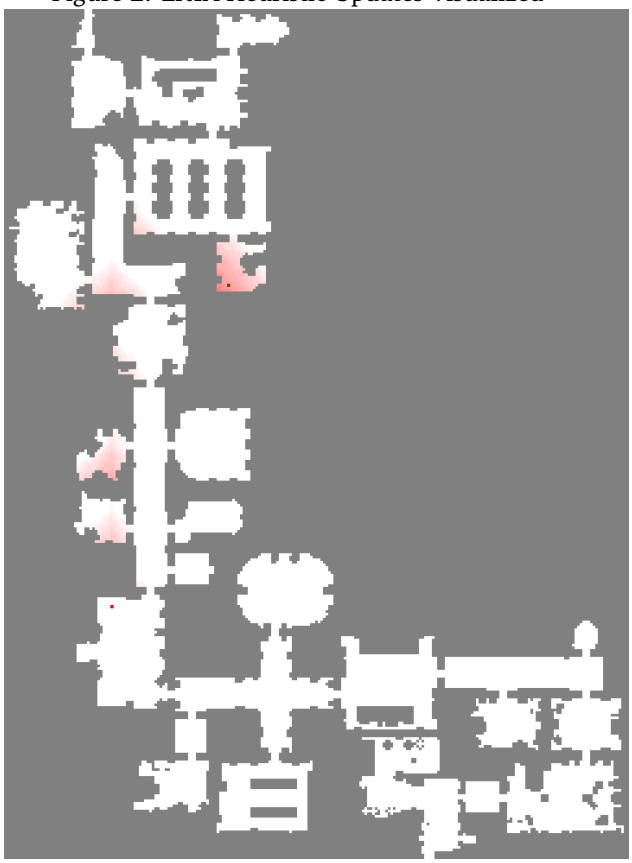


Figure 2: LRTA Heuristic Updates Visualized



with $V_{i,j}$ and $d_{i,j}$. Right now my program does this by finding the nearest neighbors in the case base and averaging them. However, this part will be replace by a neural network later.

(I also want to try predicting a move instead, we will see.)

5 Theoretical Analysis

5.1 Completeness

We keep track of the number of visitations of each state. Once the number of visitation of a certain state exceeds M, a constant that we select, then the agent plan with vanilla LRTA* on that state. Since LRTA* is complete, and our algorithm at most plans $M * numberofstates$ times, the whole algorithm is complete.

5.2 Offline Time Complexity

The time is linear to the number of cases generated.

5.3 Offline Space Complexity

Since we are training a neural network with cases, we don't need to store the cases explicitly and the cases can be discarded once the network is trained. As a result, the offline space required by the algorithm is purely based on the number of parameters of the network, which is a constant.

5.4 Online Time Complexity

Once we train a neural network for the case base, each query takes a fixed amount of computational time. Since the LRTA* backbone of the algorithm also runs in constant time, the whole algorithm runs in constant time.

5.5 Online Space Complexity

The agent only store sub-goals in its memory and the number of sub-goals is upper-bounded by the number of states in the map. Hence, the online space complexity is a constant.

6 Empirical Evaluation

Evaluate on *Dragon Age: Origins* (DAO) maps provided by Sturtevant (2012). So far I evaluated the draft version (not using a neural network) on one map and compared it with weight LRTA* ($w = 4$), and their suboptimality is roughly the same. I am planning to evaluate my algorithm on more DAO maps. In addition, I would like to split the pool of maps into a *training pool* and a *testing pool*. I will try to build the case base on the training pool and see if the algorithm works well on the testing pool.

7 Discussion

We think using a neural network to build a case base is powerful idea and has a huge potential. We can discard the collected cases after the training is done (or even discard them as we train) to achieve a constant offline space complexity. We can also have constant time look up in the case base no matter how many cases we collected. We can think of a neural network to be the ultimate way to compress information in a case base to a fixed size.

8 Future Work

One thing we would like to try is to create a neural network powered case base for querying optimal paths. The input of the network will be the start position and the goal position. The output of the network will be a sequence of hill-climbable sub-goals. Online, the agent retrieves the sub-goals and follows along by hill-climbing. Algorithms like kNN LRTA* suffers from case base offline space complexity and online time complexity. However, if we can train our case base with infinitely many cases without worrying about the consequences, we can make that infinite knowledge shines.

9 Conclusions

I expect to draw a conclusion base on my empirical evaluation.

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