Accelerated A* Path Planning
(Extended Abstract)

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Algorithms, Performance, Experimentation

Keywords

Path planning, Motion planning, Autonomous vehicle, A*, Adaptive sampling

1. INTRODUCTION

The paper addresses the area of path planning for nonholonomic vehicles operating in a large-scale dynamic continuous three-dimensional space where the vehicle has to avoid given obstacles and restricted areas. For vehicles, motion dynamics is defined by means of constraints on the driving manoeuvres and restrictions on smoothness of the trajectory[1]. The paper addresses only the basic spatial path planning problem – a process searching for a spatial arrangement of the trajectory from the given start position and orientation to the given target position and orientation. Extended problems like incremental planning are not considered by this paper. The dynamic environment means that obstacles' and restricted areas' definitions are altered almost after each particular search.

The field of the path planning problem has been studied by the research community for many decades. The problem is still topical as all intelligent autonomous vehicles have to include path planning into their deliberation mechanisms. There exist very efficient (fast) algorithms based on randomness, e.g. the random-walk planner [3], the rapidly exploring random tree (RRT) [8] and the randomized potential field [2] algorithms. Although there are many extensions of these path-finding concepts, their search processes are still based on random sampling and it cannot be said that paths generated by them are optimal with respect to a pre-specified criterion. In many cases, the path require additional smoothing to remove unnecessary random curvature from the path trajectory.

There exist algorithms providing an optimal solution for the given domains with pre-built structures for the given environment definition, e.g. the vector field [10], the potential field [5], the 3D field D* [4] and the hierarchical path-finding A* [1] algorithms. The search process of these algorithms is pretty fast but they require very expensive (especially for large-scale environments) re-building of their pre-built structures after each change in the environment. For the addressed domain it means that structures need to be rebuilt almost before each search run.

Using the original A* algorithm [7], there is a trade-off between the search speed (efficiency) and the search precision defined by the pre-specified sampling density of the continuous space (ability to find path through small gaps). There exists an extension of the A* algorithm, the incrementally refined A* [6], which iteratively repeats the search process with increased sampling density. Once the path is found, it cannot be guaranteed that there does not exist a better (shorter) trajectory going through smaller gaps. On the other hand, to check that the path does not exist it first needs to iteratively fail several times.

The novel *Accelerated A** (AA*) algorithm has the ambition to supplement existing optimization-based path planning methods for large-scale environments where the existing algorithms are unusable for their computational and memory requirements.

2. ACCELERATED A* CONCEPT

The AA* algorithm extends the original A* algorithm to be usable in large-scale environments without forgetting about the search precision. The AA* removes the trade-off between the speed and the precision by introducing of the *adaptive sampling*. During the expansion, child states are generated by applying vehicle elementary motion actions using elements' adaptive parametrization. The set of elementary motion actions is defined by the model of the nonholonomic vehicle movement dynamics. The adaptive parametrization varies so that the algorithm makes larger steps when the current state is far from obstacles and restricted areas and smaller steps when it is closer, see Figure 1.

There is a defined *search precision* specifying the minimal sampling grid step which is used in the areas closest to

[1]The smoothness means that the path is continuous as well as its first derivation.

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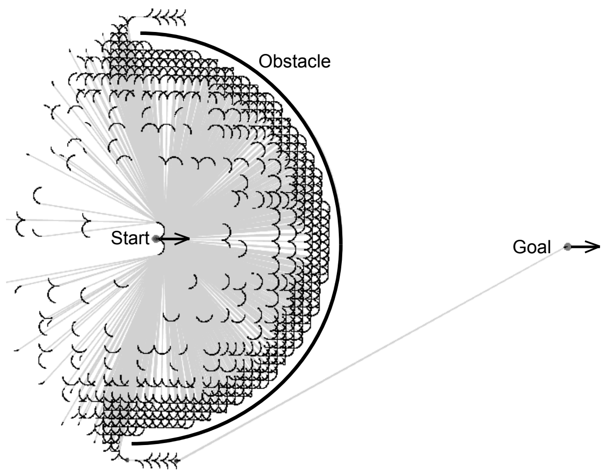

Figure 1: The adaptive sampling example in the two-dimensional setup.

obstacles. The search precision is defined so that the AA* algorithm does not skip any existing gap between obstacles larger than this precision. The adaptive parametrization sampling uses only variants which correspond to sampling sizes equal to the precision to the power of two. Specifically, the AA* algorithm uses the highest possible parametrization which ensures that the distance to the closest obstacle is not smaller than the distance corresponding to two respective sampling steps.

The adaptive sampling in the AA* algorithm requires a different definition of identity tests when working with OPEN and CLOSE lists. The original equality implementation is replaced by a similarity check. Two states are similar if their Euclidean distance and their direction vector variation is less than a threshold derived from the respective sampling parametrization. Otherwise, the adaptive sampling of a nonholonomic vehicle trajectory causes an infinite state generation in the continuous space. To remove effects of varying sampling, each path candidate generated during the search is smoothed.

The described AA* algorithm significantly reduces the number of samples (states) generated during the search in large-scale environments and it does not decrease the quality of the solution.

3. EVALUATION

Properties of the AA* concept were evaluated on a set of two and three-dimensional setups [9]. The original A* algorithm with a distance-to-target heuristics was chosen as a comparator because it is the only one which provides an optimal solution and does not require any pre-processing of the environment definition. The size of testing environments was selected at the maximum which is computable by the original A* algorithm within one hour on the standard 2.5 GHz desktop computer with 8 GB of memory. The AA* algorithm provides acceleration of the path planning up to 1400 times in comparison to the original A* algorithm. Moreover, it was found that the AA* algorithm also accelerates the failure result (the path doesn't exist) due to the reduced number of all generated states.

It was validated that the adaptive sampling does not affect the ability to also find the path through small gaps between obstacles for the given search precision. The significant state reduction implies reduction of memory requirements. This makes the AA* algorithm suitable for large-scale dynamic configuration spaces.

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