Generative Adversarial Network based Heuristics for Sampling-based Path Planning

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Abstract

Sampling-based path planning is a well known method to obtain a free-collision path to reach the goal. With this method the state space is explored uniformly, without taking into account geometrical complexities that the space could present. However, this approach presents some limitations, the most important being that the convergence speed to an optimal solution is slow.

In this paper we present a new approach to tackle these limitations, the key innovation is the introduction of a Generative Adversarial Network (GAN) to reduce the search space. The network transforms the original environment map into an environment map with a delimited region of interest which is used as heuristic to achieve non-uniform sampling for the path planner. The results show that the quality of the region of interest (ROI), the number of computed nodes and the convergence speed to a solution improves the baselines by a significant margin in most conditions. Furthermore, apart from the environments similar to the training set, our method also works well on the environments which are very different from the training set.

1 Introduction

Path planning is a well known methodology to find a sequence of valid configurations to move a robot from source to destination. The objective is to compute a free-collision path by optimizing a performance criterion like for example distance. Many classical approaches have been proposed to solve the path planning problem, such as Gradient based algorithms (Potential fields, NF1), combinatorial or exact algorithms (Dijkstra, A^*, D^*). However, there are some problems existing in these approaches such as computational difficulty and local optimality.

More recently, sampling-based algorithms(RRT, RRT^*) have shown to perform incredibly well in real world applications. These algorithms are very effective, but converging to an optimal solution could be expensive. **BlueRRT has the limitation of returning solutions far away from the optimal one and some techniques like Near Neighbour search and Tree rewiring operations could be a solution to try to solve this limitation(RRT^*).**

Nevertheless, there are also some limitations of the RRT algorithms which still remain to be solved. For example, the solutions are usually far from optimal and the asymptotic optimality [7] takes a lot of time to converge to the optimal solution.

In order to overcome these problems, we propose a novel algorithm based in Generative Adversarial Network (GAN). This novel approach was presented by Tianyi Zhang et al. [1]. In recent years, learning-based algorithms have shown promising results on path planning problems. Especially, they exhibit remarkable generalization to completely unseen environments and can easily be applied to different sizes of maps.

We leverage the already efficient RRT^* algorithm alongside the generated promising regions such that an optimal path could be found using less computation time. GAN is trained with a large amount of empirical promising region data, and its objective is to receive as input an RGB image of the environment map and to return as an output another RGB image where a promising region is delimited. This region of interest is used as heuristic to achieve non-uniform sampling for the path planner. With the results obtained, it can be clearly seen the enhancement that this new approach provides. This work, besides the results, also presents a deeper explanation about: the heuristic based RRT^*, the promising region generation and implementation details of the algorithm.

2 Related work

Recently, many researchers have proposed different types of heuristic methods to improve the performance of basic RRT algorithms.

An increasingly popular approach are learning-based algorithms as they show great advantages on path planning problems. Especially, they exhibit remarkable generalization to completely unseen environments and can easily be applied to different sizes of maps. Baldwin et al. [2] propose to learn sampling distributions by using expert data and learn an estimate of sample densities around semantic regions of interest, then incorporate them into a sampling-based planner to produce natural plans. Wang et al. [8] uses a reinforcement learning algorithm to improve the multi-RRT approach in narrow space. Even though the strategy enhances the local space exploration ability, the expansion of the searching trees is time-consuming. Ichter et al. [5] propose a general methodology for non-uniform sampling based on conditional variational autoencoder (CVAE). The weakness of this method is that sampling and planning are separated, hence the planner cannot adapt to the environment during the planning cycle.

Since the advent of GANs [4], it has been acknowledged as the most powerful generative model and widely used in various areas, such as image generation [9], image-to-image translations [3] and so on. Due to the flexibility of GANs, different architectures are proposed in recent years to tackle diverse problems. Therefore, we design a novel GAN structure to learn promising regions for achieving heuristic non-uniform sampling to improve the performance of RRT*.

3 Heuristic based RRT*

Before presenting the Heuristic Based RRT^* it is important to briefly define the basic path planning problem. Let $X \in R^n$ be the state space. The obstacle space and the free space are defined as X_{obs} and $X_{free} = X \setminus X_{obs}$ respectively. Let $x_{start} \in X_{free}$ be the initial state and $x_{goal} \in X_{free}$ be the desired state.

Let X_{goal} be the goal region where $X_{goal} = \{\ x \in X_{obs} \quad and \quad ||x - x_{goal}|| < r\}$. Path planning aims to find a feasible path σ : [0,1] $\rightarrow X_{free}, \sigma(0) = x_{start}$ and $\sigma(1) \in X_{goal}$.

Let $\sum$ be the set of feasible paths and $c(\sigma)$ be the cost function. The optimal path planning problem is to find a path σ^* with the lowest cost in $\sum$ while connecting x_{start} to x_{goal} through free space:

$$\sigma^* = \arg\min_{c \in \sum} c(\sigma)$$

$$s.t. \sigma(0) = x_{start}$$

$$\sigma(1) \in x_{goal}$$

$$\sigma(s) \in X_{free}, \forall \sigma(s) \in [0, 1]$$

As defined for X_{goal}, the cost function is based on the distance between states. $Cost(x_i, x_j) = ||x_i, x_j||$

In Sampling-based algorithms like RTT^*, the paths ($\sum$) are constructed randomly choosing samples from the free space X_{free}. This is computationally expensive, so we explored a new approach called Heuristic Based RTT^* which leverages Generative Adversarial Network (GAN) to generate regions of interest maps. This maps can be sampled using a non-uniform distribution $X_H \subset X_{free}$ reducing unnecessary sampling and improving convergence to the optimal path. This non-uniform distribution is a state space where feasible paths exist with high probability. The overview of the proposed methodology is shown in Alg. 1.

Algorithm 1 Outline of GAN-based Heuristic RRT^*

Require: x_{start}, x_{goal} and Map_{RGB}
$V = x_{start}$, $E = \emptyset$
$S \leftarrow ROIgenerator(x_{start}, x_{goal}, Map_{RGB})$
$X_H \leftarrow discretization(S)$
$G(V, E) \leftarrow HeuristicsSBP^*(x_{start}, x_{goal}, Map)$
return G(V, E)

Algorithm 2 Comparison of RRT^* and Heuristic RRT^*

Require: x_{start}, x_{goal}, H, Map_{RGB} and $UseHeuristics$
$V = x_{start}$, $E = \emptyset$
Initialize Tree with x_0
for i=1...N **do**
  if $UseHeuristics = True$ **then**
    if $Rand() > \mu$ **then**
      x_{rand} ←Non-UniformSample(X$_H$)
    else
      $x_{rand} \leftarrow UniformSample()$
    end if
  else
    $x_{rand} \leftarrow UniformSample()$
  end if
  $x_nearest \leftarrow Nearest$(G, x$_{rand}$)
  $x_new \leftarrow Steer$(x$_{nearest}, x_{rand}$)
  if Obstacle Free($x_{nearest}, x_{rand}$) **then**
    Extend (G, x_new)
    Rewire()
    if $x_{new} \in X_{goal}$ **then**
      Return G(V, E)
    end if
  end if
end for
return Failure

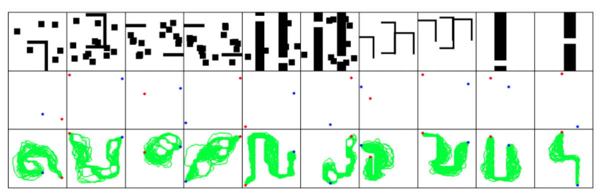


Figure 1: An illustration of the dataset. Each row from top to bottom represents maps, points, and promising regions.

4 GAN-based promising region generator

In this section, we explain in detail the proposed GAN architecture. The input of the model is an RGB image representing the map, as well as both the start state x_{init}, and goal state x_{goal}. The output of the model is also an RGB image where the region of interest is highlighted.

4.1 Dataset

The dataset includes 10000 samples of different environment maps. On each map, we randomly choose 20 to 50 different start and goal states.

In order to obtain the ground truth data for the discriminator we run the RRT* path planner for a large amount of iterations to find the optimal path. From this dataset we select 4 maps which are used for the evaluation.

4.2 Model Architecture

In fig.2 we show the overall architecture. The basic framework of GAN includes a generator G and a discriminator D. The generator accepts a sample noise z from the noise space $Z \in R$ and outputs an image $G(z)$. The discriminator is fed with images from the training data space and generated images. The generator and discriminator are in an adversarial game, such that the generator aims to fool the discriminator while the discriminator tries to distinguish the real and fake images. They are trained alternatively, which leads to the mutual growth of discernibility and generative capability.

This proposed model is based in a state-of-the-art Image-to-Image Translation GAN architecture known as pix-to-pix[6], this network learns the mapping from input image to output image in an adversarial fashion, in the path planning problem the generator learns to map world images to regions of interest. For the generator, the inputs are a 64×64 RGB map and the start and goal points. The discriminator receives the same map as the generator alongside the generated region of interest (ROI).

Tianyi Zhang et al.[1] presented a custom network specific for this task, but since the publication of this paper there have been advances in the design and optimization of GANs.

4.3 Evaluation

The two main aspects to be considered when using this network are as follows.

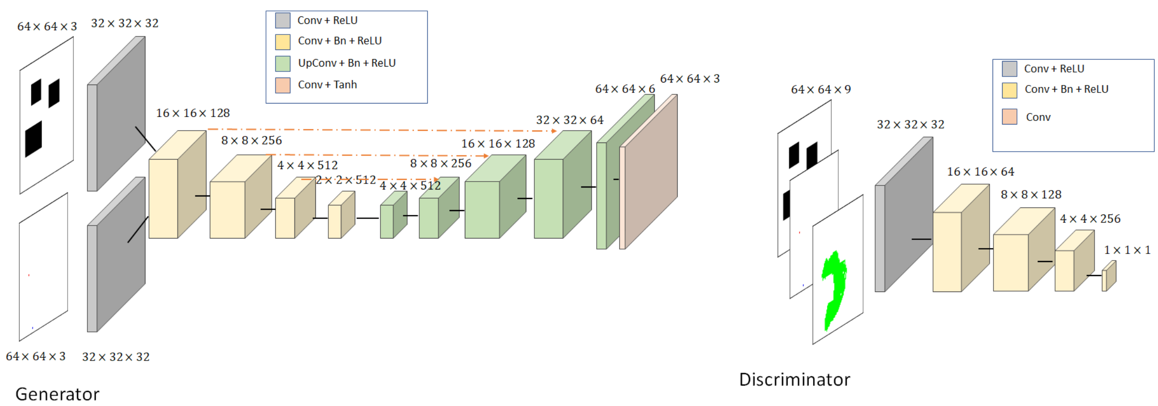


Figure 2: The overall structure of GAN model for promising region generation.

4.3.1 Connectivity

The generated region of interest can significantly reduce the exploration necessary to obtain an optimal path, but we have to study the cases were the generator fails to provide a good mapping for a given input, which causes the path planner to fail.

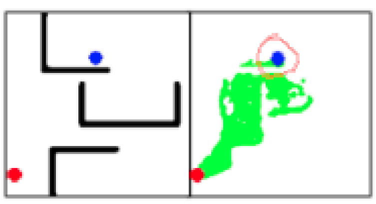


Figure 3: Example where the model fails to generate a high-quality continuous promising regions.

As we can see in figure 3, on a select number of occasions a feasible path can not be found. Overall we did not find many such cases, but it is an important limitation to consider.

4.3.2 Generalization Ability

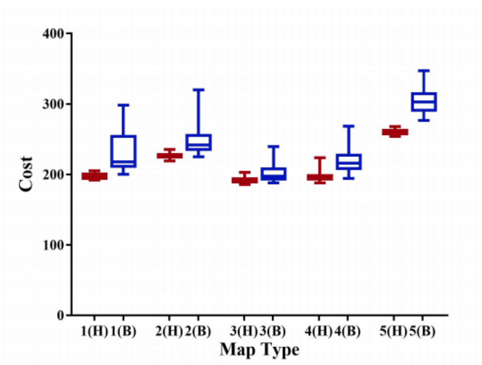
For all deep learning models it is essential to demonstrate that the model is able to generalize, showing good adaptability on unseen environments. To measure the quality of our model we test our model on unseen maps and it achieves a success rate of 81.9%.

5 Experimental Validation

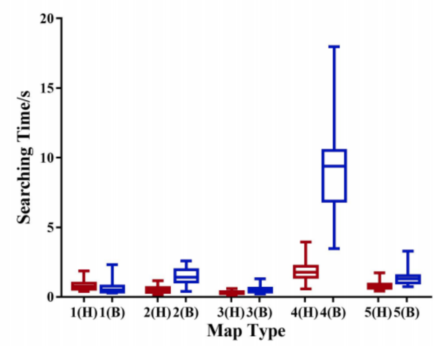
We run RRT and RRT* with ROI heuristic (non-uniform sampling) and without it (uniform sampling) for 10 times on 4 test maps. We collected the following statistics to evaluate and compare the performance of the new method: initial cost (Euclidean distance from x_init to x_goal), initial time and initial nodes expanded .

The initial stage refers to the period from the beginning to the moment when the path is found. The proposed implementation stops sampling the map once the first feasible path is found, another option could be to set a threshold for the maximum number of steps allowed in case a better path exists.

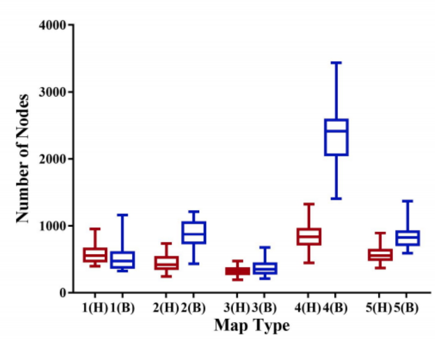
Fig. **??** displays the box-plot of the comparison on initial path cost, planing time, and the number of nodes. The midpoint of the boxes refers to average values and the height of boxes refers to variances. According to the results, the GAN based heuristic RRT* has better performance on the three tests. Additionally, the effectiveness is more obvious on difficult tasks (such as map0, the same we used in the



(a) Initial stage path cost.



(b) Initial stage time



(c) Initial stage nodes.

Figure 4: Comparison of path cost, planning time, and the number of nodes between GAN-based heuristic RRT* (H) and basic RRT* (B). The red boxes refer to the GAN-based heuristic RRT* and the blue box indicates basic RRT*.

labs). Furthermore, the heuristic non-uniform sampling distribution reduces the variance considerably, which means that it increases the robustness of RRT* to find a feasible path in a shorter amount of time. On average the quality of the paths obtained with this new approach outperform the classic methods, as the distance is usually better or the same of RRT*.

In the test maps the proposed global planner was able to always find a feasible path, but the current model performs imperfectly on generating promising regions that cross long distances. This is mainly because the long-distance paths account for a small ratio in the whole randomly-generated dataset, resulting in difficulties for the model to learn distant connections. We could fine-tune the model giving more importance to long distance paths instead of selecting them randomly.

6 Conclusion

We present a novel image-based heuristic methodology to guide non-uniform sampling-based path planning algorithms, in particular we focus on RRT*, an efficient and common option in the field of robotics.

The evaluation of the proposed GAN-based heuristic model shows significant improvement on the quality of initial paths and greatly accelerates the convergence speed to the optimum.

Furthermore, in this practical work we have studied the main limitations of this approach, such as the need for specialized hardware to run inference on the real robot, which could prevent it from being used in low budget platforms.

Many researches can be continued based on the this work. One extension is to apply the model to dynamic environments, where the input map that the generator receives changes over time as we explore the environment. Another promising modification consists in developing a more intelligent sampling strategy, which could improve the convergence speed even further.

References

[1] "Max Q.-H. Meng" "Tianyi Zhang" "Jiankun Wang". *Generative Adversarial Network Based Heuristics for Sampling-Based Path Planning.* 2022.

[2] Ian Alan Baldwin and Paul Newman. "Nonparametric learning for natural plan generation". In: *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, October 18-22, 2010, Taipei, Taiwan.* IEEE, 2010, pp. 4311–4317. DOI: 10.1109/IROS.2010.5651569. URL: https://doi.org/10.1109/IROS.2010.5651569.

[3] Anoop Cherian and Alan Sullivan. "Sem-GAN: semantically-consistent image-to-image translation". In: *2019 ieee winter conference on applications of computer vision (wacv).* IEEE. 2019, pp. 1797–1806.

[4] Ian Goodfellow et al. "Generative adversarial nets". In: *Advances in neural information processing systems* 27 (2014).

[5] Brian Ichter, James Harrison, and Marco Pavone. "Learning Sampling Distributions for Robot Motion Planning". In: *2018 IEEE International Conference on Robotics and Automation (ICRA).* 2018, pp. 7087–7094. DOI: 10.1109/ICRA.2018.8460730.

[6] Phillip Isola et al. *Image-To-Image Translation With Conditional Adversarial Networks.* 2017.

[7] Sertac Karaman and Emilio Frazzoli. *Sampling-based algorithms for optimal motion planning.* 2011.

[8] Wei Wang, Lei Zuo, and Xin Xu. "A Learning-Based Multi-RRT Approach for Robot Path Planning in Narrow Passages". In: *J. Intell. Robotics Syst.* 90.1–2 (May 2018), pp. 81–100. ISSN: 0921-0296. DOI: 10.1007/s10846-017-0641-3. URL: https://doi.org/10.1007/s10846-017-0641-3.

[9] Mengyao Zhai et al. "Lifelong gan: Continual learning for conditional image generation". In: *Proceedings of the IEEE/CVF International Conference on Computer Vision.* 2019, pp. 2759–2768.