Multi-Robot Space Exploration System Controlled by Auction Mechanism

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Abstract

This study proposes a multi-robot space exploration system. A market mechanism is introduced to control the path planning and collaboration of multiple robots, and robots will exchange unexplored areas through bidding, thereby exploring a given space in an efficient manner. This study utilizes implicit neural representation to record the spatial environment around the robot, essentially training a function to represent the spatial and geometric features around the robot when depth information is available. Since it is a multi-robot system, distributed optimization is used to fit this function. This multi-robot system can complete space exploration more efficiently than a single-robot system. The bidding mechanism allows the system to flexibly introduce new robots, and the damage of a single robot will not affect the operation of the entire system. Implicit neural representations can record the explored environment as a continuous function with very little memory.

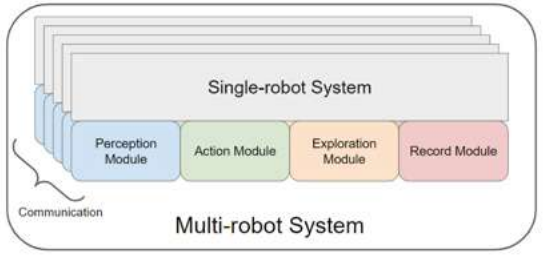
Motivation

In recent years, due to the development of self-driving cars and metaverse industry, the demand for 3D environment reconstruction is increasing. Implicit Neural Representation is a function that can record 3D space with very low-cost memory. Since it is a neural network in nature, it makes me think that if we train Implicit Neural Representation with distributed optimization, we no longer need to centralize data on the same machine before we can start training. This property is very suitable to be applied in a multi-robot system. Therefore, This study investigates whether an implicit neural representation can be combined with an auction mechanism so that it can travel through a given space in the most efficient way.

Purpose

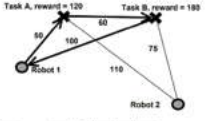
This study investigates whether an implicit neural representation can be combined with an auction mechanism so that it can travel through a given space in the most efficient way. Previous multi-robot exploration systems based on auction mechanisms have used other methods to record its environment, and the recording method affects the robot's decision making when planning future paths.

Methodology



Exploration Module - Auction Mechanism

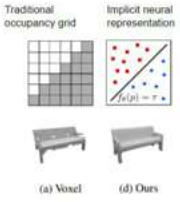
Definenition :
Cost: distance a robot travel
Revenue: information a robot generate



Each robot generate a list of goal points → Each robot tries to auction their goal points → Each robot travel to its goal point using D*

Repeat

Record Module - Occupancy Network



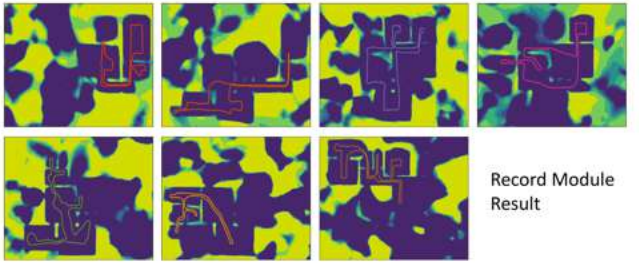
- Images: $f : \mathbb{R}^2 \to \mathbb{R}^3$, $f(x, y) = (r, g, b)$.
- Videos: $f : \mathbb{R}^3 \to \mathbb{R}^3$, $f(x, y, t) = (r, g, b)$.
- Voxels: $f : \mathbb{R}^3 \to \{0, 1\}$, $f(x, y, z) = p$ where $p = 0$ for an empty voxel and $p = 1$ for an occupied voxel.

Each robot generate a list of goal points → Each robot tries to auction their goal points → Each robot travel to its goal point using D*

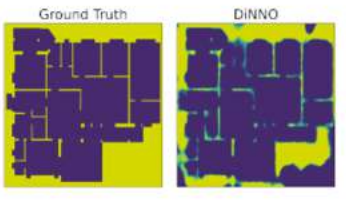
Exploration System Flow Chart

Record environment with INR → Train INR with distributed optimization

Results



Record Module Result



Use distributed optimization for training

Conclusions

In the simplified two-dimensional scenario, this study has demonstrated the use of implicit neural representation as a recording module for a multi-robot system, using seven robots to train a forward propagating neural network together with the data collected by the simulated radar to represent a planar map in the CubiCasa5K dataset. The investigation of using bidding mechanism to control a multi-robot system is still under research. It is expected to combine the exploration module and record module in the future.

Future Development

In addition to the experiments in the simulated environment, this study is also conducted in real life. this study tries to use a self-assembled mobile robot to prove the system could work in real-life scenarios.

References

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[4.] Javier Yu, Joseph A. Vincent, Mac Schwager(2021). DiNNO: Distributed Neural Network Optimization for Multi-Robot Collaborative Learning.