# Pushing and Grasping robot arm with Self-supervised Reinforcement Learning

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### Summary

- Our project will be investigating in synergizing grasping and other movements of a simulated robot arm, by using deep reinforcement learning methods, to improve the arm's intelligence. The project is based on existing research, which will make our project more feasible. It stimulates our interest because most of the researches on robot arms have not mentioned synergies of various kinds of movements.
- The goal of this article is mainly to complete visual grasping through machine learning. Therefore, the background and related data we investigated can be divided into four aspects, namely visual recognition, simulated reality, self-supervision, and reinforcement learning. Through the background information of these aspects, understand the current development and research status of this technology. Through comparative research, we can find innovative points in this article. It is good for us to learn from this and carry out our own projects.
- When collecting data of simulation part: Non-prehensile manipulation (Pushing): non-uniform friction distributions across object surfaces, the variability of friction; Grasping: a database of known 3D object models, visual features (i.e. shape, pose, dynamics). When it comes to experiments, we will focus on Simulations results on random arrangements; Grasping performance vs. Numbers of training steps; Completion rate, Success rate and Action efficiency of different methods
- For State Representations, we model each state  $s_t$  as an RGB-D heightmap image representation of the scene at time t. To compute this heightmap, we capture RGB-D images from a fixed-mount camera, project the data onto a 3D point cloud, and orthographically back-project upwards in the gravity direction to construct a heightmap image representation with both color (RGB) and height-from-bottom (D) channels.
- To evaluate the result of grasping, the completion rate is obviously the most important indicator, a good result of learning is expected to have a high completion rate. In the meantime, other results should be taken into consideration, such as grasp success rate and action efficiency. For the result, I expect figures rather than plots, but using the figure to draw a plot is a good way of showing how well the robot perform. I will compare my result of different index (as mentioned above) with other way of learning or operation using tables

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## What is the problem that you will be investigating?

Our project will be investigating in synergizing grasping and other movements of a simulated robot arm, by using deep reinforcement learning methods, to improve the arm's intelligence.

The project is based on existing research, which will make our project more feasible. It stimulates our interest because most of the researches on robot arms have not mentioned synergies of various kinds of movements.



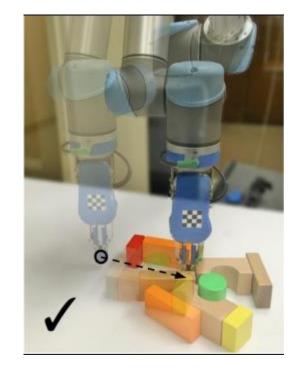
## What reading will you examine?

The goal of this article is mainly to complete visual grasping through machine learning.

Therefore, the background and related data we investigated can be divided into four aspects, namely visual recognition, simulated reality, self-supervision, and reinforcement learning.

Through the background information of these aspects, understand the current development and research status of this technology.

Through comparative research, we can find innovative points in this article. It is good for us to learn from this and carry out our own projects.





## What data will you use?

### **For Simulation:**

Non-prehensile manipulation (e.g. Pushing): non-uniform friction distributions across object surfaces, the variability of friction

Prehensile manipulation (e.g. Grasping): a database of known 3D object models, visual features (shape, pose, dynamics)

### For experiments:

Simulations results on random arrangements

Grasping performance vs. Numbers of training steps

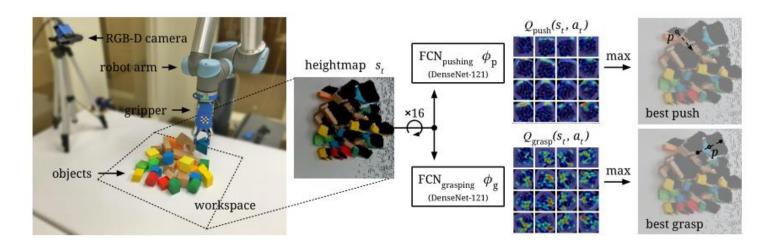
Completion rate, Success rate and Action efficiency of different methods



## What method or algorithm are you proposing?

### **State Representations**

We model each state  $s_t$  as an RGB-D heightmap image representation of the scene at time t. To compute this heightmap, we capture RGB-D images from a fixed-mount camera, project the data onto a 3D point cloud, and orthographically back-project upwards in the gravity direction to construct a heightmap image representation with both color (RGB) and height-from-bottom (D) channels.





## What method or algorithm are you proposing?

### **Primitive Actions**

We parameterize each action a t as a motion primitive behavior  $\psi$  (e.g. pushing or grasping) executed at the 3D location q projected from a pixel p of the heightmap image representation of the state  $s_t$ :  $a = (\psi, q) | \psi \in \{\text{push}, \text{grasp}\}, q \rightarrow p \in s_t$ 

Our motion primitive behaviors will mainly focus on Pushing and Grasping.

Q-learning FCNs trained by using the Huber loss function:

$$\mathcal{L}_i = egin{cases} rac{1}{2} \Big( Q^{ heta_i}(s_i,a_i) - y_i^{ heta_i^-} \Big)^2, ext{ for } \Big| Q^{ heta_i}(s_i,a_i) - y_i^{ heta_i^-} \Big| < 1, \ \Big| Q^{ heta_i}(s_i,a_i) - y_i^{ heta_i^-} \Big| - rac{1}{2}, ext{ otherwise.} \end{cases}$$



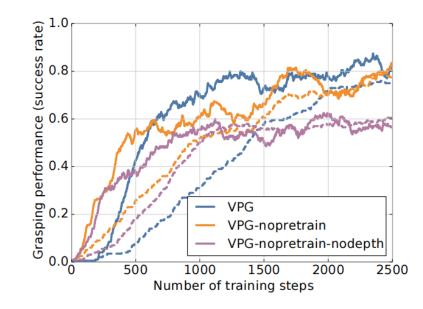
### How will you evaluate your results?

To evaluate the result of grasping, the completion rate is obviously the most important indicator, a good result of learning is expected to have a high completion rate. In the meantime, other results should be taken into consideration, such as grasp success rate and action efficiency. For the result, I expect figures rather than plots, but using the figure to draw a plot is a good way of showing how well the robot perform. I will compare my result of different index (as mentioned above) with other way of learning or operation using tables.

#### TABLE IV

REAL-WORLD RESULTS ON CHALLENGING ARRANGEMENTS (MEAN %)

Method	Completion	Grasp Success	Action Efficiency
Grasping-only [8]	42.9	43.5	43.5
VPG	71.4	83.3	69.0





# Thank You



