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Mobile robot avoid obstacles using Monocular Vision

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Technical Aspects of Multimodal Systems

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Outline

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Motivation: Why use Monocular Vision

In the paper *Deep Learning* from Nature: [LeCun et al., 2015][1]

> *The future of deep learning: Unsupervised learning had a catalytic effect in reviving interest in deep learning, we expect unsupervised learning to become far more important in the longer term. Human and animal learning is largely unsupervised: we discover the structure of the world by observing it, not by being told the name of every object.*

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- Cheap
- Easy to get
- Flexible to complicated environments

Disadvantage

- Not as accuracy as depth sensor
- Need a lot of calculate power
- Need a lot of training
- Not stable in current time

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Related Work: Use Traditional Ways

In the traditional way of doing obstacle avoidance task, one should use the camera to detect the point flow to get the information about the environment. For example,the position of the floor and obstacles. Then we can use some fixed way to plan and executes.

- Use Depth camera to get Point Cloud
- Use the Point Cloud to fitting a function about the ground
- Calculate the distance between every point with the fitting ground h
- If h is larger than a setting threshold, then marke it as an obstacle
- Transfer the Point Cloud data of the obstacle to the robot coordinate space
- Combine the current robot moving stats with the obstacle to decide how to avoid the obstacles

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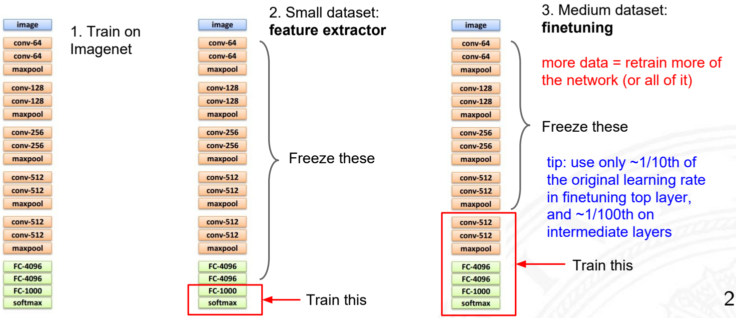
Related Work: Use CNN and transfer learning

Transfer Learning with CNNs



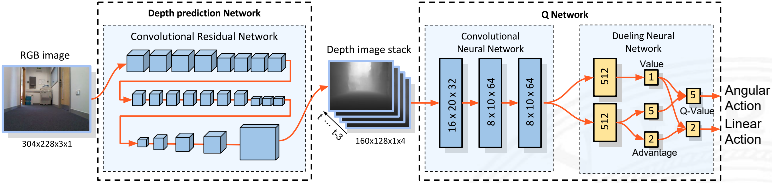
[2]

Use transfer learning (Fine tune) is also a good way to improve the training process.

[2] http://cs231n.stanford.edu/slides/2016/winter1516_lecture11.pdf

Related Work: Using CNN and reinforcement learning

[Xie et al., 2017] Towards Monocular Vision based Obstacle Avoidance through Deep Reinforcement Learning. [3]



This paper uses CNN to get a "Depth Image stack", then uses D3QN to get action.

[3] https://arxiv.org/abs/1706.09829

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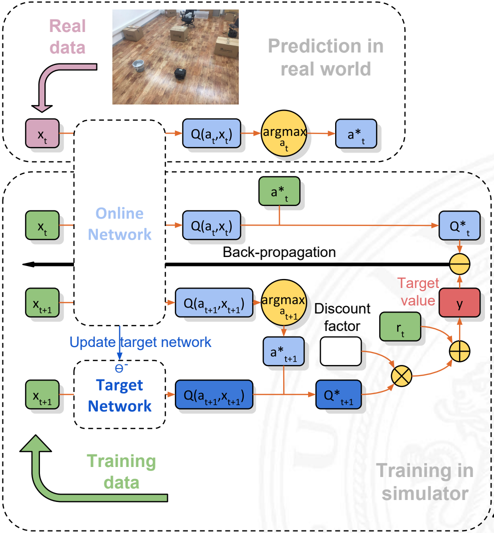

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Pipeline:

- Collect data and labeling
- Build CNN to train
- Get the result in test set

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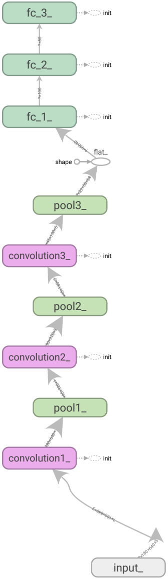

Framwork of the CNN

- Convolutional Networks
  - Conv 1: filter 16, kernel size 5, strides 1
  - Conv 2: filter 32, kernel size 5, strides 1
  - Conv 3: filter 54, kernel size 5, strides 1
- Fully connected Networks

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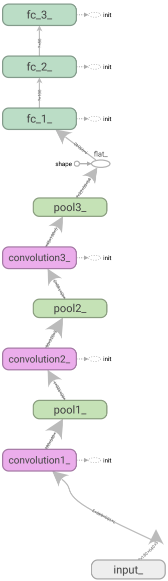

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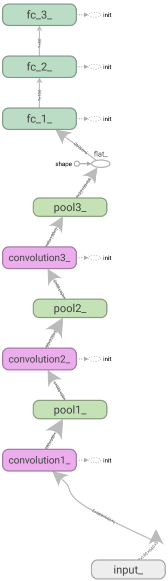

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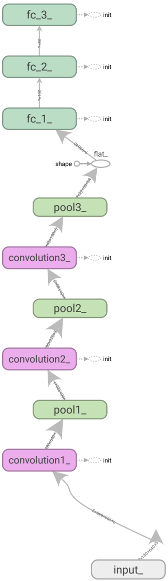

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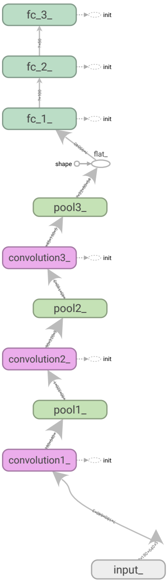

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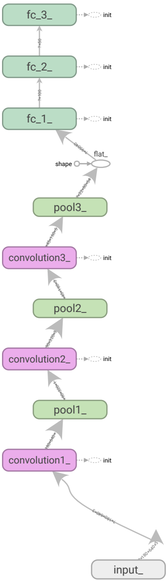

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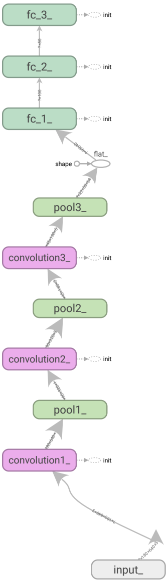

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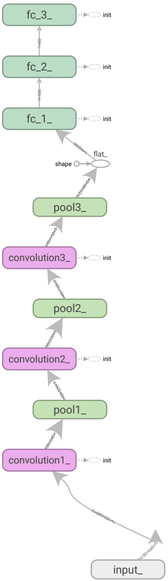

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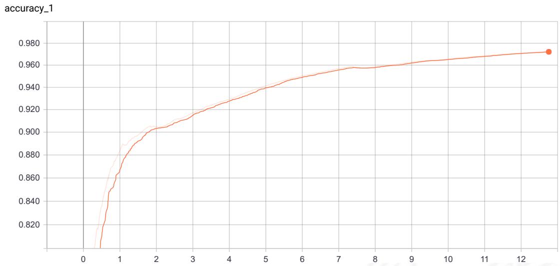

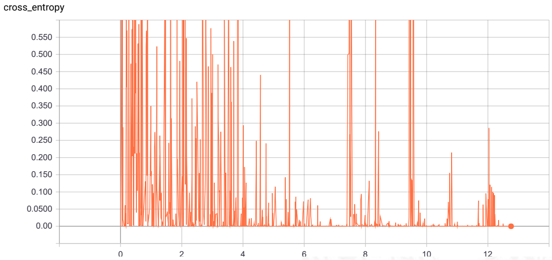

Use self supervised learning

The basic idea of this is to let robot get labels by the additional sensing such as range finder or collision detection switch. But this way is highly relying on the labeling rules.

- Using depth sensor to get "ground truth"
- Using the bumper in front of the turtlebot

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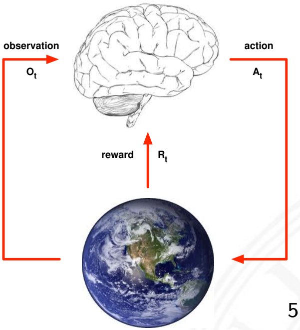

[5]

At each step t the agent:

- Executes action A_t
- Receives observation O_t
- Receives scalar reward R_t

The environment:

- Receives action A_t
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[5] http://www0.cs.ucl.ac.uk/staff/D.Silver/web/Teaching.html

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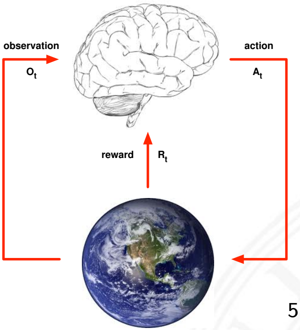

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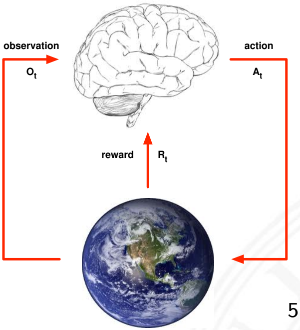

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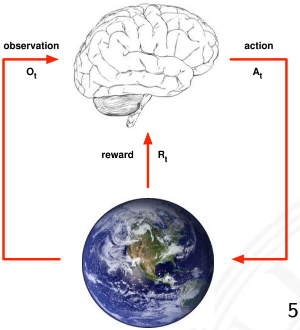

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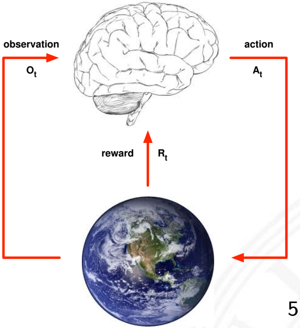

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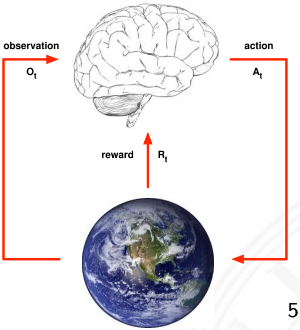

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Use Reinforcement Learning: Q-Learning

The mission of RL is to find a *best policy* in order to make the reward more.

The value function(Bellman Function) describes how to get the value of current state, that is,

$$V(s) = \mathbb{E}[R_{t+1} + \lambda v(S_{t+1}) | S_t = s]$$

To update the Q value, that is,

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \lambda \max_a Q(S_{t+1}, a) - Q(S_t, A_t))$$

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In the Q-Learning we give a Q table:

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s_4	Q(4,1)	Q(4,2)	Q(4,3)	Q(4,4)

Due to store too many states in one Q table is unrealistic in DQN, we get Q table from a network.

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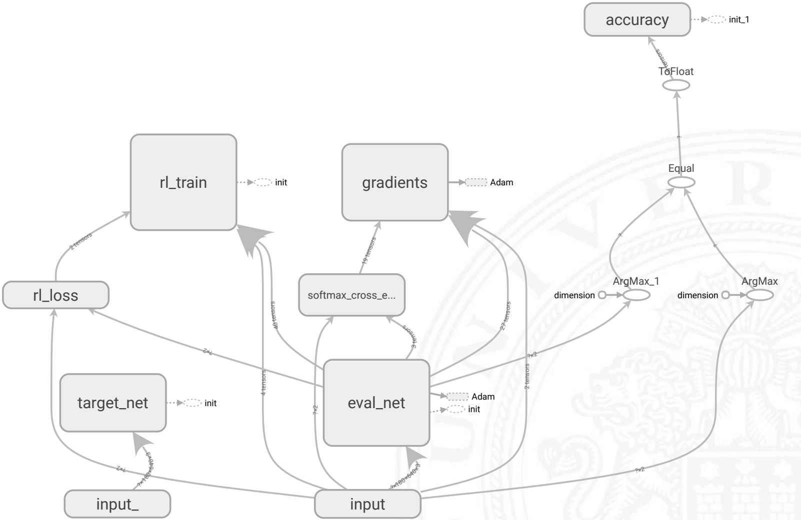
Use Reinforcement Learning: DQN Algorithm



Use Reinforcement Learning: Get Reward

```
def get_reward(self, action):
    if self.flag == action:
        if action == 0:
            reward = 1
        else:
            reward = 0
    else:
        reward = -1
    return reward
```

Flag is whether the robot is crashed a bumper. In the future, we need to add more actions.

Outline

Experiment using CNN

Experiment 2

Experiment using DQN

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- By using CNN the Monocular camera can get very good result in both training data and test data. But it will get bad result in unknown environment.
- Self-supervised learning can reduce the backward of the pure CNN, by self collecting data on the run.
- By using CNN to get a predict depth image then use this as input to train the RL network is very interesting, and it avoid the backward of using bad simulated camera in simulation environment.
- Using DQN to train the network directly is more intelligence, need to do Some furthermore researching on it.

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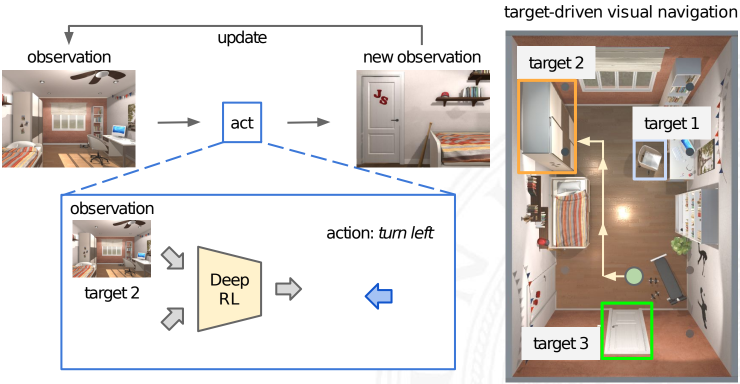
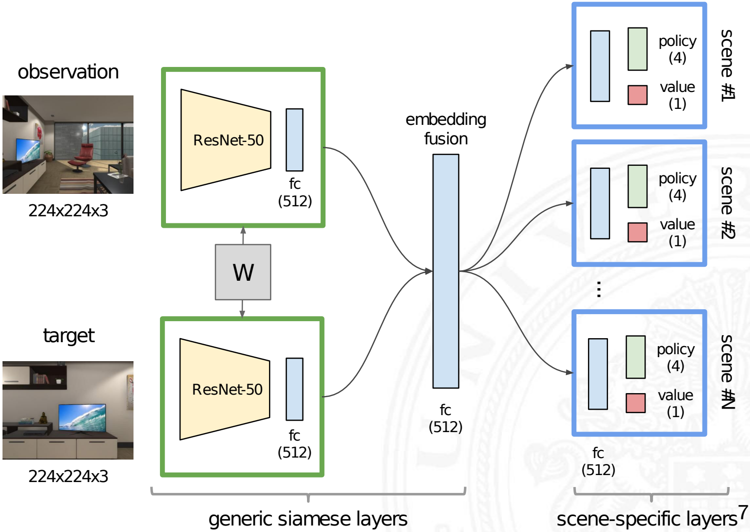
[Zhu et al., 2016] Target-driven Visual Navigation in Indoor Scenes using Deep Reinforcement Learning [6]



[6] https://arxiv.org/pdf/1609.05143.pdf

Future Work



[7] https://arxiv.org/pdf/1609.05143.pdf

Outline

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2. Details
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6. Bibliography

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Thank you for your attention,
Suggestion, Questions and
Commands are highly welcome.