My little document

August 20, 2016

Contents

1 root

1.1 Reinforcement Learning

1.1.1 Q Learning

$$Q(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \left(\overbrace{\underbrace{r_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}}^{\text{learned value}} - \underbrace{Q(s_t, a_t)}_{\text{old value}} \right)$$

1.2 The video

`https://www.youtube.com/watch?v=z0gSC---rgM`

The video illustrates a car learning to avoid obstacles. As shown in Figure 1, the environment is a 2D scenario. The whole scenario is surrounded by fences. There are 4 irregularly shaped obstacles. To show the learned ability generalizes well with different layouts of obstacles, the obstacles will revolve about the center of the room slowly, at a constant speed, during running.

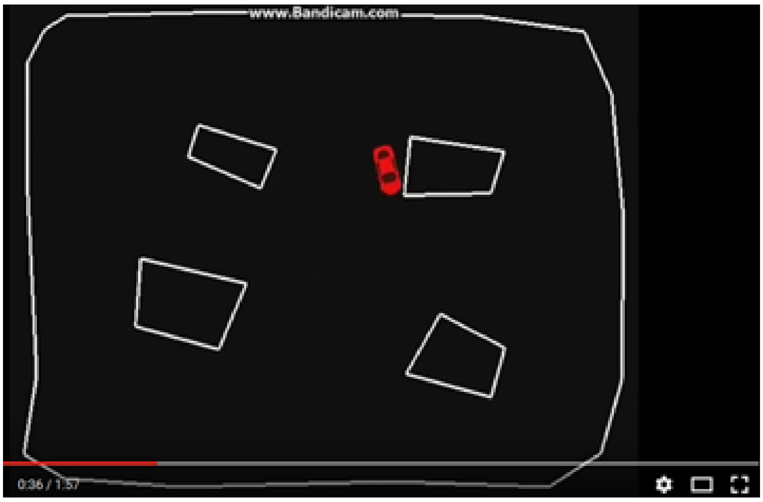
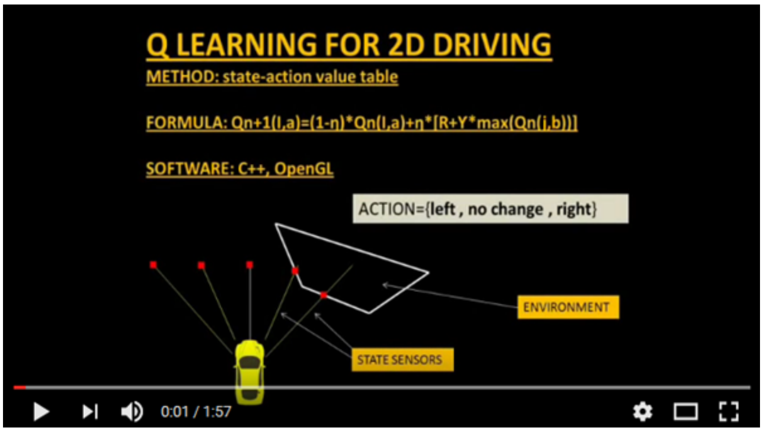


Figure 1: youtube$_{\text{screenshot}}$

For each period, the car starts from the center of the room, with a randomly chosen direction. Its action is controlled by a reinforcement learning algorithm. During the early periods, the actions are like randomly decided. When the car runs into obstacles or fences, it will be repositioned to the center of the room, and a new period begins. The car learns over time.


Q LEARNING FOR 2D DRIVING

METHOD: state-action value table

FORMULA: Qn+1(I,a)=(1-n)*Qn(I,a)+n*[R+Y*max(Qn(j,b))]

SOFTWARE: C++, OpenGL

ACTION={left , no change , right}

Figure 2: youtube$_{\text{structure}}$

The illustration comprises two parts, a 2D environment described above, and a learning algorithm which controls the action of the car. The algorithm learns from and makes decisions on specified data provided by the environment. The environment emulates 5 state sensors, corresponding to 5 different direction in front of the car. These sensors find the nearest obstacle, and measure the distance from the obstacle to the car. The distance information is transferred to the car in the form of a 5D vector. During running, the algorithm will predict an action based on the distance information and then feed it back to the environment, to control the movement of the car.

1.3 Re-Implementation

For our further research, we need a verified code base to start with. So we want to implement the application in this video.

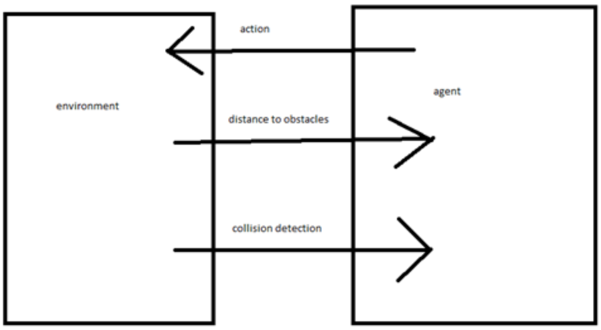


Figure 3: structure

The implementation takes 3 steps.

- Build an environment.
- Implement a reinforcement learning algorithm to control the car.
- Provide and transfer learning data and actions between the environment and the algorithm.

1.3.1 Reinforcement Learning

We started this part with a project on Github.com. In further research, we will build a variant algorithm of the deep q network. So we choose this implementation of deep q network as the code base of our reinforcement learning algorithm. This implementation is written in python, and based on Theano and Lasagne.

Paper `http://arxiv.org/abs/1312.5602`

Code `https://github.com/spragunr/deep_q_rl`

Adaptation The deep q network takes the raw images of a game as its inputs to predict actions. The network includes convolutional layers to handle the image data. But the current environment provides only distance information, in the form of a vector, instead of the raw images. So we replaced the convolutional neural network with a simple multi-layer neural network, to handle the distance information.

1.3.2 The Environment

We choose to build this 2D environment on a real-time 3D rendering engine. It is for the convenience of later transition. Because our later goal is to train the car to avoid obstacles in 3D environments.

Panda3D The 3D rendering task is assigned to Panda3D, a game development environment. It is written in C++ and supports both C++ and python.

Intra Process Communication In future research, it is required to frequently transfer raw images from the environment to the learning model. Since we will write both programs in python, the data can then be transferred as an intra-process pointer. This will be convenient and efficient.

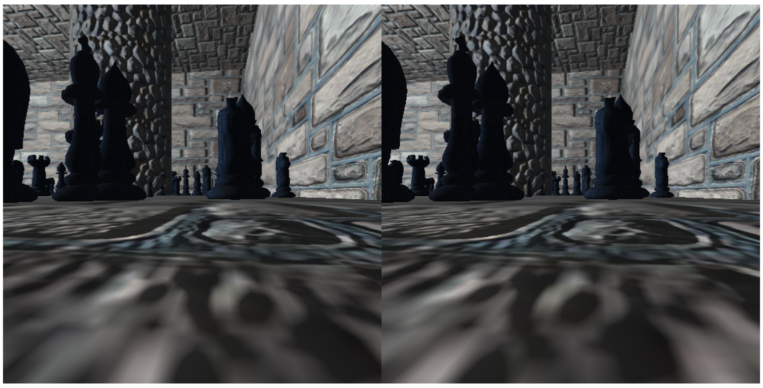


Figure 4: A 3D view

Layout As shown in Figure 4, the scenario is located in a cubic room. A round pole is fixed at the left bottom corner (Figure 5). And a square pole is fixed at the top right corner. 200 chess pieces are randomly positioned in the room.

1.3.3 Learning Data

a Extracting depth maps (Goal: E (distance) =¿ Q) Convenient Method: depth map =¿ distance ,(`https://en.wikipedia.org/wiki/Depth_map`) (Figure 2). What is depth map? Figure ??? How to generate from 3d models How to extract distance from depth map. Figure ???

,(Figure 3),,agent ,agent,agent. Figure 1: agent, Figure 2: depth map generated from 3d models Figure 3: o Reimplement q-learning o Feeding distance to q-learning Different Implementaion o Data: volume??

1.3.4 Training

Random Actions

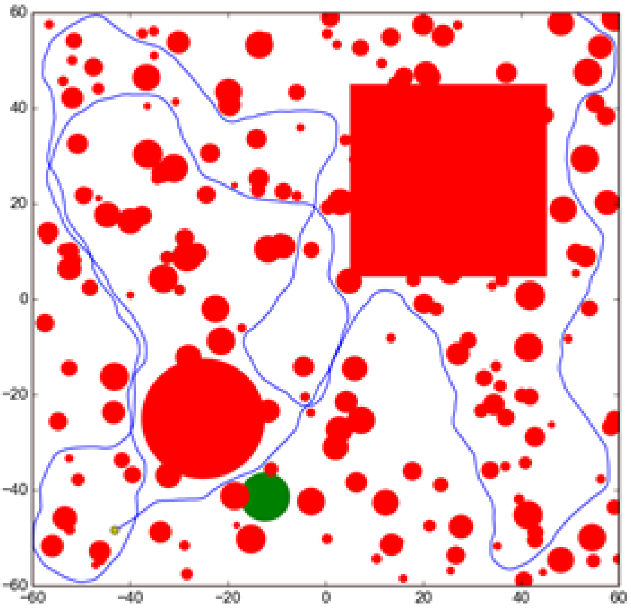


Figure 5: A top-down view. Red shapes represents obstacles. (mark the poles later)(Green circle/blue lines remove later) Green destination(remove)Blue line routes (remove)

1.3.5 Results and discussion:

,agent. .

Problems . ,agent.. ,agent