ISSN 2706-655X Vol.5, Issue 5: 1-7, DOI: 10.25236/IJFET.2023.050501

Research on the robotic arm modeling algorithm based on deep learning

Hongkun Xiang[1], Lihua Huang[2], Tianyu Lan[1], Jun Wang[1], Yan Zhao[1], Binlong He[1]

[1] *School of Intelligence Technology, Geely University of China, Jianyang, Chengdu, Sichuan, 641400, China*
[2] *School of Electronic and Information Engineering, Geely University of China, Jianyang, Chengdu, 641400, China*

Abstract: *We propose a Deep learning which is to be aimed at the method of robotic arm modeling algorithm. Firstly, the movement of the mechanical arm, raise the traditional intelligent grasping system, improve the SSD original model, and enhance the backbone network performance selectively, improve the depth of the applicability of deterministic strategy gradient (DDPG) algorithm for further research, to shorten the mechanical arm model debugging time to reach the goal of avoiding obstacles according to research on the mechanical arm dynamics modeling.This will make the robotic arm to have a high ability to adapt to the environment, and can provide researchers with ideas to solve the theoretical research and engineering implementation in this field after training and learning.*

Keywords: *robotic arm; deeplearning; kinetic modeling; SSD algorithm; DDPG algorithm*

1. Introduction

The development of artificial intelligence technology has given birth to intelligent robots, which are more adaptable to the environment and, driven by intelligent algorithms, can make reasonable decisions according to the real environment, reduce the knowledge and experience dependence of human experts with stronger adaptability to the environment. The mechanical arm has multiple elements such as perception, movement and decision-making, and can integrate the real scene information to make the most reasonable action, which is more in line with the needs of social development.

In recent years, deeplearning (DL) has developed in areas of gaming, autonomous driving, and intelligent healthcare. Deep learning enables agents to possess the similar to the human mind by imitate humanity, then through combining with hardware, it has the ability to perceive environmental information and make decisions about empirical data. At present, deep learning has been widely used in the field of robotic arm control. Deep learning and conventional control theory complement each other, providing a new idea for the intelligent control of robotic arm motion planning method based on deep learning.

2. Dynamic modeling of manipulator

2.1 Dynamic modeling

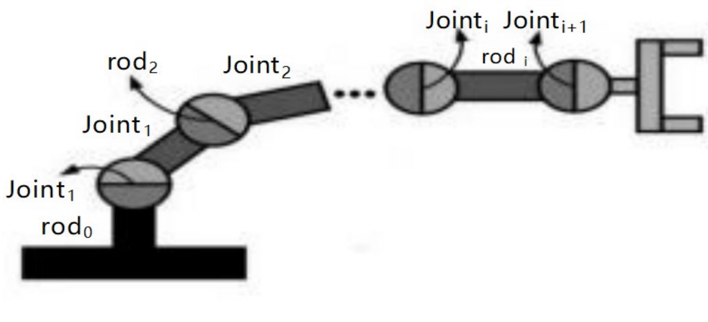

Figure 1: Diagram of robotic arm

ISSN 2706-655X Vol.5, Issue 5: 1-7, DOI: 10.25236/IJFET.2023.050501

The main purpose of dynamic modeling of a robotic arm is to obtain the joint torque during the motion of the robotic arm. The method for defining joints and links is shown in Figure 1. In a series mechanical arm structure, the mechanical arm is composed of a rotating joint and a movable joint. The base is called a connecting rod 0 that is not included in the connecting rod. The connecting rod 1 is connected to the base by a joint 1, the connecting rod 2 is connected to the connecting rod 1.

E_k, E_p are required in the total kinetic energy E_k and the total potential energy E_p of the robotic arm system to find their difference L=E_k -E_p in the Lagrangian method, and finally to establish the Lagrangian kinetic equation:

$$F(i) = \frac{d}{d_t} \times \frac{\partial_L}{\partial_{Q_i}} - \frac{\partial_L}{\partial_{Q_i}}$$

i = 1,2,..., n (i is the complete constraint equation of number value) formula: Q_i is the generalized system coordinate; Q_i is the corresponding generalized velocity; F_i is a system of generalized forces; n is a complete number of constraint equations.

2.2 DH system

The DH system and DH parameters represent the coordinate system and coordinate parameters between two adjacent members, which are connected by joints. The structural parameters are a_k, c_k, α_l,define the fixed value between two adjacent joints, and the motion parametersφ_k is the amount of joint movement.

Craig in the monograph[1] introduce the improvement method of establishing DH system. The physical significance of improving DH department is more clear in the theoretical derivation, which is convenient for engineers[2].

The improved DH system is called the DH system, and its definition is shown in Figure 2: Given joint K-1 and joint K, the following is the pedigree process for improving the DH system:

Make the rotation axis of the joint (k-1) and the joint (k) is z_{k-1},z_k, respectively.

1) Make a vertical line between z_{k-1},z_k,is x_l, the intersection of $x_l z_{k-1}$is o_k.the intersection of x_l. z_k is o_1.

2) The distance between o_{k-1} and o_k are marked c_k.

3) The distance between o_k and o_l is α_k.

4) The Angle between the axis z_{k-1} and z_k is α_l.

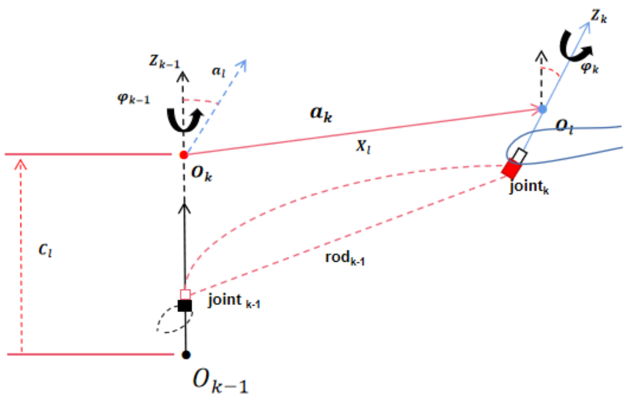

Figure 2: DH line and DH parameters

3. Modeling of robot arm motion planning based on deep learning

Researchers have attempted to break the correlation between empirical data through traditional experience playback mechanisms to ensure stable convergence of the algorithm, endow the robot with learning and cognitive abilities, enable it to learn and demonstrate movement [3], and thereby independently complete the generalist.

ISSN 2706-655X Vol.5, Issue 5: 1-7, DOI: 10.25236/IJFET.2023.050501

Currently, research on robotic arm control based on deep learning can achieve good experimental results in simulation environments, however, when migrating to a real robotic arm, the experimental results are generally poor.

On one hand, there are many interferences and noises in the real environment due to the differences between the simulation environment and the real environment. On the other hand, direct training on a real robot arm can cause some physical losses.

This section provides a robot arm motion planning method and system based on deep learning, in order to solve the problem that deep learning algorithms are difficult to deploy from a simulated environment to a real environment in the prior art.

3.1 Deep learning

Deep learning is mainly divided into three categories: convolutional neural networks, feedback depth networks, and bidirectional depth networks[4].

The convolutional neural network mainly adopts the bottom-up empirical learning training method, while the feedback depth network mainly adopts the top-down prior learning method, the convolutional neural network combined with the first two training methods is a reverse thinking, bidirectional deep network.

Deeplearning focuses on perceiving and expressing things, and its core idea is to map low-level data features into high-level representations that are easy to handle, discover the connections and characteristic representations between data through multi-layer network structures and nonlinear transformations.

Deeplearning uses multi-layer structures to abstract data features to build computational models, and sufficiently complex structures can handle high-dimensional raw data. Some researchers have conducted in-depth research on the field of robot operation based on deep learning: Du Xuedan et al[5], proposed a robotic arm grasping method based on deep learning algorithm. Wu Xiru et al[6]CNN used to conduct image processing to locate the target, and the six-axis flexible industrial sorting robot verifies that the recognition accuracy of the model can reach 98%. In addition, deep learning has been successfully used by robots to push target objects, operate a 3-dimensional object model And operating containers for the dumping of the liquid And so on task.

3.2 Mechanical arm movement planning

After years of research, the motion planning algorithm of robotic arm can solve most of the operation tasks of robotic arm, but it still faces two challenges: motion planning in complex obstacle environment and high dimensional planning space online planning. Motion planning algorithm, trajectory optimization algorithm, heuristic algorithm, and artificial potential field method. Figure search motion planning algorithm has more advantages over other traditional motion planning algorithms in complex obstacle environment; motion planning algorithm and trajectory optimization algorithm have more advantages in online planning of high-dimensional planning space. The motion planning algorithm of high-dimensional planning space has become a research topic in recent years, the motion planning algorithm has attracted more attention and scalable high-dimensional motion planning algorithm is proposed[7], And the accessible space algorithm[8], Discrete RRT algorithm[9]isosampling motion planning algorithm and trajectory optimization algorithm can realize online fast replanning, but the planning efficiency is limited by the initial trajectory quality and planning dimension.

Domestic and foreign scholars have carried out lot of studies, mainly including the common motion planning methods of robotic arms, such as polynomial interpolation method, spatial linear method, spatial arc method, etc[10].

4. SSD algorithm

SSD is a popular and powerful target detection network, which contains the underlying network, auxiliary convolution layers and prediction convolutional layers. In 2016, WEILIU proposed in ECCA, the SSD algorithm belongs to the One-stage algorithm, which emphasizes the direct regression method to quickly calculate the position and category of targets.

ISSN 2706-655X Vol.5, Issue 5: 1-7, DOI: 10.25236/IJFET.2023.050501

4.1 Default box evaluates the rules

The size of the feature graph receptive fields in different layers in the convolutional neural network is also different, and here different regions and target sizes are used to correspond to the default box of different positions.

Feature maps at different levels can also feel different domain sizes in convolutional neural networks, which are represented here by default squares with different regions and target sizes corresponding to different positions. With M feature maps used to predict, then the following size of the default block in each feature graph is:

$$s_i = s_{min}[\frac{s_{max}}{m-1} - \frac{s_{min}}{m-1}](i-1), i \in [1,m] \quad (1)$$

Formula (1): in the network structure s_{min} is the default bottom box scale, the value is 0.2;s_{max} is the highest level of the default border scale, the value is 0.95. follow this formula $a_r \in \{1,2,3,1/2,1/3\}$to find the width and height of the default box respectively:

$$\omega_i{}^a s_i\sqrt{a_r}= \quad (2)$$

$$h_i{}^a s_i\sqrt{a_r}= \quad (3)$$

The central point of setting a default box is $\left(\frac{i+0.5}{|fk|}, \frac{j+0.5}{|fk|}\right)$, where, i,j$\in$[0,|fk|],|fk|, is the size of the k feature graph.The features of different sizes, aspect ratios of all default boxes are extracted to predict the results, and the results are integrated to solve the problem of target detection at different scales.

4.2 Basic structure of the SSD

Backbone network: consisting of some convolutional layers in VGG 16, replacing the Conv 6 and Conv 7 of the last two layers with a fully connected layer for image classification. It is characterized by multiscale Feature map prediction, with a total of six Feature map inputs into the NMS for merging and screening. And for each layer to perform the Default Bounding Box extraction.

SSD is detected using a CNN network with multiscale feature maps of the infrastructure shown in Figure 3 below.

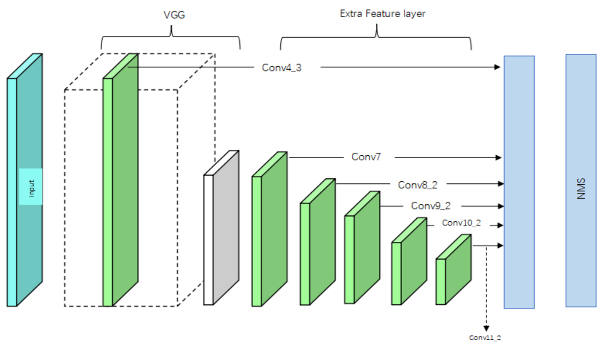

Figure 3: Basic architecture of the SSD

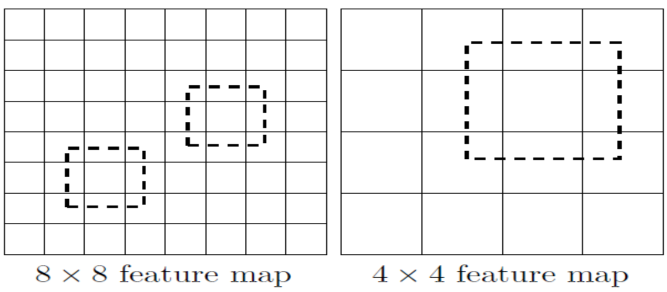

Figure 4: CNN network feature diagram

The so-called multi-scale uses the feature graph of different sizes, CNN network generally the previous feature graph is relatively large, and then gradually use convolution or stride=2 of POLOLING

ISSN 2706-655X Vol.5, Issue 5: 1-7, DOI: 10.25236/IJFET.2023.050501

layer to reduce the size of the feature graph. As shown in Figure 4: (the feature map of 8x8 can be divided into more units, but the prior box scale of each unit is relatively small, so its prior box scale is relatively small, so its prior box scale)

4.3 Mechanical arm modeling based on the SSD algorithm

SSD is based on VG-16, changing the full connection layer after CONV 5 to convolution layer, in which the feature graph output by CONV 4 _ 3 is 3838, and then CONV 8, CONV 9 and CONV10 are added after FC7, a powerful target detection algorithm with good real-time and high detection accuracy. Conv11, form a complete solid state disk network.

SSD builds the model for the infrastructure, and the front end of the model adopts the VGG 16 network structure for extracting low-scale feature map as the basic feature extraction network; the back end reduces the dimension of the feature map extracted by the front-end network layer by layer, and uses the deviation of different convolution layers, so as to realize the feature map prediction at multiple scales and an additional multi-scale feature detection network.

The RSSD (Rainbow SSD) model, by improving features fusion, combining pooling and deconvolution operations, detects more small proportion of targets, and improves the detection accuracy of MAP by 1.3% over the SSD model, which is basically the same as the DSSD model.

FSSD (Feature Fusion SSD) model, its detection accuracy MAP is 0.3% higher than the RSSD model, 0.2% higher than the DSSD model, and 1.6% higher than the SSD model. Since this model is a lightweight feature fusion module with a detection speed closer to the SSD model, its detection performance surpasses many state-of-the-art target detection algorithms.

5. DDPG algorithm

5.1 Basic principles

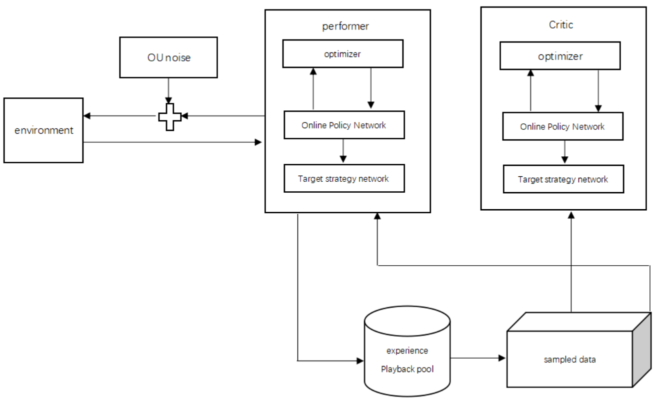

Figure 5: Network framework diagram of the DDPG algorithm

DDPG uses an actor-critic algorithm framework with different strategies, using a dual network structure similar to Double deep-Learning Network (DDQN) to solve the problem of slow convergence. In the DDPG algorithm, Smart interacts with the environment to obtain the state, the action strategy is obtained through the neural network, Smart performs the strategy after the environment feedback, and then the strategy is evaluated through the decision ability of deep learning, and then the neural network (New Network) is updated. The DDPG algorithm network structure is shown in Figure Figure 5[11].

5.2 DDPG algorithm process

The process of training machine path planning using the DDPG algorithm is shown in Figure 6.

ISSN 2706-655X Vol.5, Issue 5: 1-7, DOI: 10.25236/IJFET.2023.050501

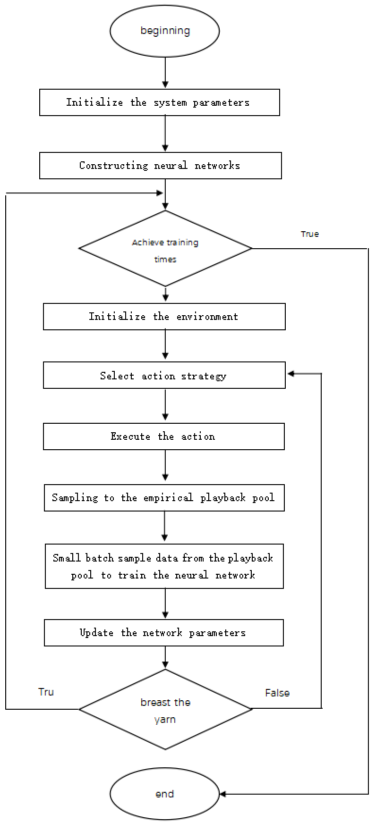

Figure 6: Flow chart of the DDPG algorithm training program planning the machine path

5.3 Mechanical arm modeling based on the DDPG algorithm

The fault tolerance control of the arm adopts the deep deterministic strategy gradient (DDPG) algorithm for the movement performance of the arm itself.

DDPG introduces deep learning into the continuous action space, which can solve the continuous action problem. Compared with the traditional control method, the deep learning control method can make full use of intelligent technology to explore the optimal control path and avoid the process of repeated debugging of the control system. The deep learning control method can determine the control strategy in a short time, which is more efficient than the traditional method. As a model-free control method, it can realize a variety of different categories of motion control with strong applicability.

In the robotic arm task, the target object needs to reach a specific position to get rewarded. In order to speed up the convergence rate, a DDPG algorithm is proposed, combined with multi-object learning to achieve the control of the two-link mechanical arm. The virtual target "L" is set to replace the original target. When the single segment training ends and the end does not reach the target object L, the robotic arm can also get rewarded quickly by reward and speed up the learning speed in the initial stage of training. The overall algorithm flow, as shown in Algorithm 1.

DDPG

1) The parametric weight is the random initialization of Theta q and Theta μ critic, the random initialization of Q_s and the Seta μ critic networks of Aeta q and actor networks;

2) Initialize the target network $\theta_{Q'}\leftarrow\theta_Q, \theta_{\mu'}\leftarrow\theta_\mu$ with the parametric weightsQ' and μ'

3) Initialize the experience playback area;

4) Start with the number of sets episode=1 and train M sets:

5) Initialize the random process noise and conduct action exploration;

6) Obtain the initial observation status;s_1

7) Start with steps t=1 and cycle training T steps:

8) Random noise selection according to current strategy and exploration process:

$$a_t = \mu(\theta^{\mu})=+\text{Noise};$$

9) Reward in the environment, action a_t, and the new environment state s_{t+1};

10) If t=T-1 and the end does not reach the target, use the end position instead of the original target, recalculate s_t, r_t, s_{t+1}

11) Store the data obtained from the action execution (s_t, a_t, r_t, s_{t+1})into different experience pools according to the reward size;

12) Random sampling of data of N1 and N2 numbers from experience to placement pool 1 and 2 respectively (s_t, a_t, r_t, s_{t+1});

13) Update the target network (targetNet): τ + (1- τ), τ + (1- τ);$\theta^{Q'}\theta^{Q}\theta^{Q'}\theta^{\mu'}\theta^{\mu}\theta^{\mu'}$

14) adjust the size of N1 and N2 if episode%100=0.

In Algorithm 1, step 10 is to replace the original target position with the end position, and recalculate the state and reward when a specific number of steps and the target object is not reached, steps 11-12 are the storage sum of the experience pool, and steps 13-14 are the learning process of Web Model.

6. Future research direction

At present, the target detection algorithm based on deep learning is in the stage of rapid development, and many new theories, new methods and new applications are derived from it. With the improvement of the performance of the target detection algorithm and the promotion of its application, the future research direction is summarized as follows:

How does the backbone network performance improve? Powerful feature extraction capability of deep learning is the key to success, a deep learning-based object detection algorithm. It is mainly reflected in two aspects of accuracy and performance, namely the influence of backbone network on the performance of target detection algorithm.

References

[1] Craig J J. Introduction to robotics: mechanics and control[M]. India: Pearson Education, 2009.

[2] Shin S, Kang H J, Lim H K, et al. Robot calibration and modified command generation for the offline programming [C]. International Conference on Mechatronics Technology, 2007

[3] Lieto A, Bhatt M, Oltramari A, et al. The roleof cognitive architectures in general artificial intelligence [J]. Cognitive Systems Research, 2018, 48:1-3

[4] Yin Baocai, Wang Wentong, Wang Lichun. Review of deep learning studies [J]. Journal of Beijing University of Technology, 2015 (1).

[5] Du X D, Cai Y H, LuT, et al. A robotic grasping method based on deep learning[J]. Robot, 2017, 39(6): 820-828, 837.

[6] Wu X R, Huang G M, Sun L N. Fast visual identifification and location algorithm for industrial sorting robots based on deep learning[J]. Robot, 2016, 38(6): 711-719.

[7] Luna R, Moll M, Badger J, et al. A scalable motion planner for high-dimensional kinematic systems [J]. The International Journal of Robotics Research, 2020, 39(4):361-388.

[8] McMahon T, Thomas S, Amato N M. Sampling-based motion planning with reachable volumes for high-degree-of-freedom manipulators [J]. The International Journal of Robotics Research, 2018, 37(7): 779-817.

[9] Solovey K, Salzman O, Halperin D. Finding a needle in an exponential haystack: discrete RRT for exploration of implicit roadmaps in multi-robot motion planning [J]. The International Journal of Robotics Research, 2016, 35(5): 501-513.

[10] Niku S B. Introduction to Robotics [M]. Upper SaddleRiver: Prentice Hall Professional Technical Reference, 2001. 103-18

[11] Lillicrap T P, Hunt J J, Pritzel A, et al. Continuous control with deep reinforcement learning[J]. arXiv preprint arXiv:1509.02971, 2015.