# Research on Object Grasping Prediction Model of Flexible Robotic Arm Based on Feedforward Neural Network

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**Abstract:** Object grasping is the core part of robot automation, which has irreplaceable value in the fields of industrial assembly, logistics sorting and service robot. However, the coupling effect of the physical characteristics of the object and the operating parameters in the actual scene leads to a significant fluctuation in the grasping success rate of the flexible manipulator, and the traditional method is difficult to achieve accurate prediction. Therefore, this paper proposes a prediction model of object grasping of flexible manipulator based on feedforward neural network. The model takes the two-dimensional position of the object, the grasping force, the angle and the type of the object as the input features. Through the adaptation of the double hidden layer structure to the ReLU and Sigmoid activation functions, the grasping success probability is output, and the two-class cross entropy loss and Adam optimizer are used to improve the training efficiency. The experimental results show that the accuracy is 89.2 %, and the mean square error is 0.073. It can effectively reveal that the success rate of grabbing items with handles is significantly higher than that without handles, and the stability can be improved by horizontal angle and moderate high intensity.

**Keywords:** Feedforward Neural Network; Flexible Robotic Arm; Object Grasping; Success Probability Prediction; Operation Parameter Optimization

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## Introduction

The field of automated production and intelligent services has already equipped a large number of high-precision and high-reliability robotic grippers, which have become the core execution components in scenarios such as industrial assembly[1]. Whether it is the assembly of precision parts in automobile manufacturing, the sorting of multi-category goods in e-commerce logistics, or the picking and placing of daily items by home service robots, all rely on flexible robotic arms to achieve efficient and safe gripping operations [2] .

However, the complexity of actual grasping scenarios and the significant differences in the physical properties. Whether there is a handle directly affects the stability of the grasping force point, while the surface smoothness determines the distribution of friction during the grasping process, thus affecting the grasping reliability[3].At the same time, the selection of operating parameters is also crucial. Deviations in the grasping angle, excessive or insufficient force, and slight shifts in position coordinates may all lead to grasping failure. The coupling effect of these factors makes the grasping success rate fluctuate significantly in different scenarios[4]. This paper constructs an accurate prediction model that can comprehensively consider the influence of multiple factors to improve the grasping stability and efficiency of flexible robotic arms in complex scenarios.

## 1 Literature Review

Traditional mechanical models construct dynamic equations based on physical contact and force analysis. They have good interpretability in standardized, but require high accuracy of physical parameters and are difficult to cope with complex scenarios with multiple factors coupled. The solution process is easily affected by uncertainty [5].Among the classic machine learning models, decision tree models are efficient in training and have an intuitive structure, but they have insufficient generalization ability and are prone to overfitting. SVM can handle nonlinear correlation problems, but the selection of function and parameter tuning depend on experience. They are less efficient in high-dimensional features and large-scale datasets and are difficult to meet the real-time grasping requirements [6] .

Neural networks have become a hot topic in grasping tasks due to their powerful nonlinear mapping capabilities. FNNs can automatically learn the potential correlation between parameters by constructing a multi-hidden layer structure and taking structured parameters such as position, force, and angle as inputs. They have shown the advantages of simplicity and efficiency in predicting the probability of successful grasping [7]. CNNs are good at extracting visual features of objects and can achieve end-to-end prediction by fusing visual information with operational parameters. Various models have verified their application value in different scenarios, but there are limitations in their applicability and feature utilization [8] .

## 2 Relevant Theoretical Basis

### 2.1 FNN

In this study, FNN contains 5 neurons: the object's 2D position ( x,y ), grasping force, grasping angle, and object type . The hidden layer is the core of feature extraction and dimensionality transformation. Through weighted summation and activation operations of neurons, it maps the input features to a high-dimensional feature space . This model has 2 hidden layers, each with 64 neurons. Neighboring neurons are fully connected, forming a dense network structure to achieve deep feature representation. The output layer maps the high-dimensional features processed by the hidden layers to the target output. In this study, the output layer has 1 neuron, used to output the grasping success probability. The hidden layer uses the ReLU function. The output layer uses the Sigmoid activation function.

The model training optimizes the algorithm to minimize the deviation between the predicted and true values, using BCELoss as the loss function. The mathematical expression is as follows:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

Where N represents the number of samples, $y \in \{0,1\}$ represents the true label of the i th sample, and p represents the success probability of the model's prediction. The optimizer uses the Adam algorithm, combining the advantages of Momentum and RMSProp.

## 2.2 Key Influencing Factors of Capture

Whether a flexible robotic arm can successfully grasp an object essentially depends on the balance of contact forces and the constraints of friction. These factors can be categorized into two main types: the characteristics of the object and the operating parameters.

Therefore, objects with handles can provide a clear rigid support point. The flexible robotic arm forms a "point-to-surface" constraint structure by gripping the handle, and the force can be evenly distributed along the handle axis, effectively dispersing local stress and reducing the risk of slippage due to uneven force. Objects without handles rely on the full contact between the robotic arm and the object surface to generate friction to maintain grip . The force distribution tends to concentrate in local areas and is easily affected by the object's center of gravity shift, resulting in significantly reduced stability. Surface smoothness affects gripping reliability by changing the coefficient of friction. Smooth-surfaced objects have a lower coefficient of friction, resulting in limited static friction under the same gripping force, requiring precise control of operating parameters to avoid relative slippage. Rough-surfaced objects have a higher coefficient of friction and more abundant static friction reserves, but irregular surface textures may cause force concentration at the contact point, increasing the probability of gripping posture deviation, especially in handle-less scenarios where this negative impact is more significant.

Among the operational parameters, the gripping angle, force, and position coordinates directly affect the gripping result by altering the contact mechanics. The optimal gripping angle is horizontal, where the robotic arm's gripping surface is in complete contact with the object's surface, maximizing the contact area and distributing the normal force along the object's center of gravity, thus maximizing static friction. As the angle increases, the contact area gradually decreases, and the force direction deviates from the center of gravity axis, easily generating additional torque that can cause the object to flip or slip. The gripping force is positively correlated with static friction. According to Coulomb's law of friction, static friction is $f_s \leq \mu_s N$. However, excessive force may cause object deformation or overload of the robotic arm joints, while insufficient force may fail to overcome the object's gravity and inertia, leading to gripping failure. The influence of position coordinates is reflected in the relative relationship between the gripping point and the center of gravity of the object: when the gripping point is close to the center of gravity of the object, the object is in force balance and its posture is stable. If the gripping point deviates too far from the center of gravity, it will generate additional torque that will disrupt the force balance, and even if other parameters are optimized, it will easily lead to gripping failure.

# 3 Experimental Results and Analysis

## 3.1 Experimental Setup and Evaluation Indicators

To verify the performance of the object grasping prediction model of the flexible robotic arm based on FNN, this experiment constructed a dataset covering multiple types of objects and multiple operational parameters. The dataset contains four types of objects. The samples of each type of object cover the full range of combinations of position coordinates ($X \in [-1.5, -0.8]$, $Y \in [-1.5, -0.5]$), grasping angle (0~3 radians), and grasping force (1~10), generating a total of 10,000 valid samples, which are divided into a training set (7,000 samples) and a test set (3,000 samples) in a 7:3 ratio.

Table 1 Model Parameter Table

| parameter | describe | value |
|---|---|---|
| Input layer | coordinates, gripping force, angle, and object shape. | 5 neurons |
| Hidden layer | The first hidden layer contains 64 neurons and uses the ReLU activation function. | 64 neurons |
| Hidden layer | The second hidden layer contains 64 neurons and uses the ReLU activation function. | 64 neurons |
| Output layer | Output the probability of successful crawling | One neuron, Sigmoid activation function |
| loss function | Binary cross-entropy loss | BCELoss |
| Optimizer | Training using the Adam optimizer | Learning rate = 0.001 |
| Training cycle | Total number of training rounds for the model | 1000 |

The object is divided into four states: with handle - smooth surface (Type: 0), with handle - rough surface (Type: 1), without handle - smooth surface (Type: 2), without handle - rough surface (Type: 3).

Table 2 Top Ten Crawling Locations and Crawling Probability

| Position X | Position Y | Grasping Probability | Angle | Force | Item Type |
|---|---|---|---|---|---|
| -0.97902364 | -0.95959582 | 0.4015 | 0.76 | 8 | 3 |
| -1.13636916 | -0.67251166 | 0.1298 | 2.89 | 2 | 3 |
| -0.95813047 | -0.52017064 | 0.1746 | 2.44 | 2 | 3 |
| -1.01195262 | -1.12266223 | 0.3035 | 2.36 | 6 | 2 |

| | | | | | |
|---|---|---|---|---|---|
| -1.28653734 | -1.38833291 | 0.6162 | 1.65 | 10 | 3 |
| -1.00597574 | -0.85170035 | 0.7385 | 0.58 | 4 | 1 |
| -1.16270524 | -0.9880643 | 0.3374 | 2.15 | 3 | 0 |
| -1.14739206 | -1.21033096 | 0.6931 | 1.46 | 9 | 0 |
| -1.18505486 | -1.15942608 | 0.5671 | 0.81 | 9 | 2 |
| -1.00292005 | -1.15625042 | 0.5756 | 2.64 | 10 | 2 |

The data shows that the success rate of grasping ranges from 0.1298 to 0.7385, with higher success rates generally associated with greater force and a more horizontal grasping angle.

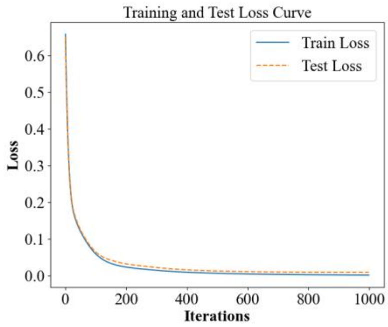


Figure 1 Iteration curve

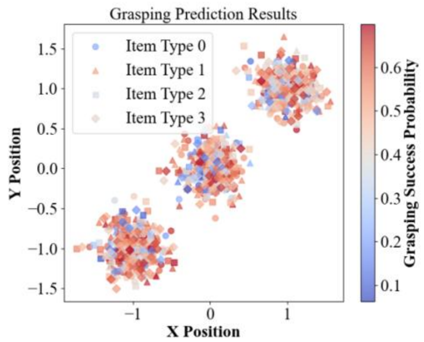


Figure 2 Scatter plot of prediction results

Figure 2 shows the distribution of different item types on the X and Y axes. Objects with smooth handles and rough handles generally exhibit a higher probability of successful grasping, while objects without smooth and rough handles exhibit lower. The physical properties of an object significantly affect the likelihood of successful grasping.

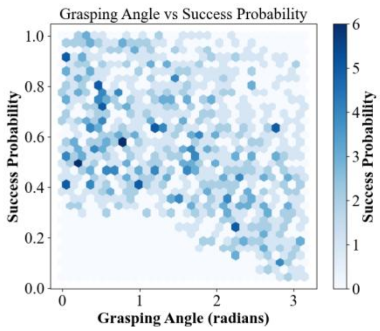


Figure 3 Probability heatmap of capture angle

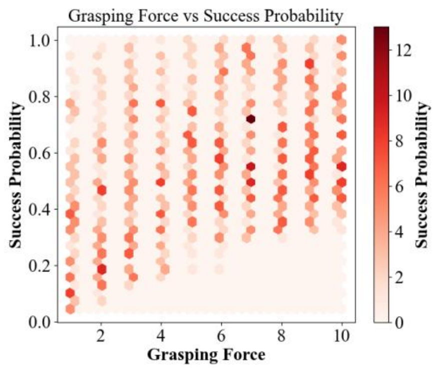


Figure 4 Heatmap of grabbing force

As Figure 3 , the success rate gradually increases as the grasping angle approaches horizontal, forming a significant trend. The success rate is generally high, especially near 0 radians, while it gradually decreases as the angle increases. This phenomenon is consistent with the grasping patterns observed in actual operation, indicating that horizontal grasping is easier to succeed, while large-angle grasping is more challenging.

As Figure 4, the X-axis represents gripping force, while the Y-axis represents the corresponding probability of successful gripping. As the gripping force increases, the probability of success gradually increases, especially at higher forces, where the likelihood of successful gripping increases significantly.

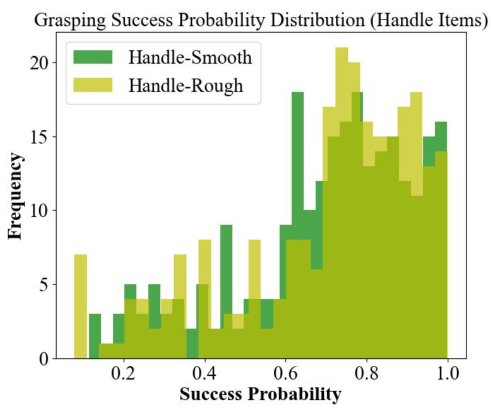

Figure 5 probability distribution chart of gripping based on whether the handle is smooth or rough

Histogram 5 shows the success rate distribution of handle-smooth and handle-rough. The success rate for handle-smooth items is relatively high, concentrated between 0.5 and 1.0, especially within the 0.6 to 0.8 range, indicating a higher probability of successful grasping. In contrast, the success rate for handle-rough items is more dispersed, mainly concentrated between 0.2 and 0.6, indicating a relatively lower probability of successful grasping.

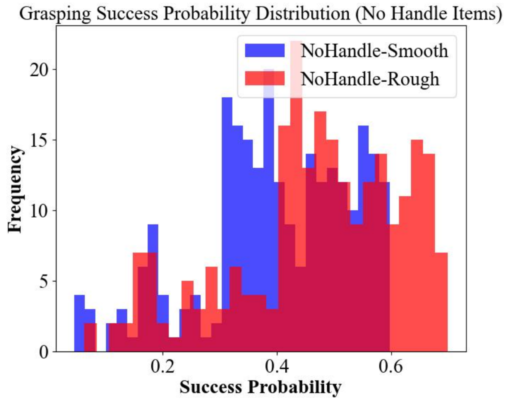


Figure 6 Grab probability distribution of smooth and rough handle categories

Histogram 6 shows the success rate distribution of No-Handle-Smooth and No-Handle-Rough. Items without handles, regardless of whether the surface is smooth or rough, result in a lower grasping success rate. Compared to items with handles, items lacking handles are more challenging to grasp, especially rough-surfaced items, whose success rate is significantly lower than that of smooth-surfaced items.

## 4 Conclusion

Aiming at the problem of success rate fluctuation caused by multi-factor coupling in the grasping scene of flexible manipulator, this study proposes a grasping success probability prediction model based on FNN, which effectively solves the problem of insufficient adaptability of traditional methods. However, in the research process, the model does not include key features such as item weight and shape complexity, and the classification of item types is simplified. In the future, the feature dimension and data set will be further enriched, the multi-modal model will be constructed by integrating visual features, and the reinforcement learning will be introduced to realize the real-time optimization of dynamic parameters, so as to promote the engineering landing of the model in practical scenarios such as industrial assembly and logistics sorting.

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