Grasping Model Identification for ZJUT Hand

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Abstract—A new type of air-driven multi-fingered dexterous hand, named ZJUT Hand, is proposed. ZJUT Hand has good passive flexibility and can make up for the deficiency of existing dexterous hands in some ways. A new method for grasping model identification based ANFIS is proposed. Simulation experimental results show that the method can easily establish the model of the target objects, and has very good recognition accuracy and convergence. Equivalent rules of target objects are presented and greatly improve the efficiency of identification. A general grasp planning program of multi-fingered dexterous hand is proposed. Finally, the grasp planning experiments for ZJUT Hand is completed. Experimental results show that ZJUT Hand is able to construct the models of two typical target objects.

Keywords—Flexible pneumatic actuator FPA, ZJUT Hand, Grasping model, Hyperelliptic equation, ANFIS

I. INTRODUCTION

The robot multi-fingered pneumatic dexterous hand which is driven by flexible pneumatic actuator (such as PMA, and FMA[1-5], etc.) has better passive flexibility and certain passive compliance to the target object, due to the reasons that the actuator itself mainly consists of rubber and better compressibility of air. The grasping targets of agricultural harvesting robot are always crisp, tender and easy to be damaged, which requires the end-effectors of the robot should have good flexibility[6]. So, the flexible pneumatic dexterous hands are widely used in the agricultural harvesting robot[7].

In recent years, a flexible pneumatic dexterous Hand (named ZJUT Hand) driven by a new kind of flexible pneumatic actuator FPA is developed[8-13]. The characteristics of this hand are as follows. 1) The mechanical parts and FPAs of the joint are integrated. Driven by FPA directly, no additional power transfer devices (such as cables, gears and artificial tendons) are needed, thus the friction is small and the vibration can be avoided. 2) Because the joint torque is output directly, the fingertip output force can be controlled easily. 3) FPA has greater specific power. Except for above advantages, ZJUT hand also has characteristics of simple structure, good adaptability, great passive compliance and adequate grasp rigidity. When ZJUT Hand is to grasp the target object, grasping model of the target object should be reconstructed. In this paper, precision grasp of ZJUT Hand is discussed, a new method for grasping model identification based ANFIS is proposed and the grasp planning experiments for ZJUT Hand is completed.

II. FLEXIBLE PNEUMATIC ACTUATOR FPA AND ZJUT HAND

From 2002, based on the shortcomings of existing pneumatic actuator, a new kind of flexible pneumatic actuator, named FPA, is proposed by in Zhejiang University of Technology. The structure and the photo of the FPA are shown in Fig.1. The static and dynamic models of the FPA were built, and the static and dynamic characteristics were experimentally tested. As shown in Fig.1 (a), FPA is composed of a rubber tube, two covers, a pipe connector and a helical steel wire embedded in the wall of the rubber. Each end of rubber tube is sealed by a cover. As shown in Fig.1 (b), to prevent air leakage, each end of rubber tube is installed a clip. The pipe connector and one of the covers are linked by threaded connections. Compressed air can fill into the FPA by the pipe connector.

Fig.1 Flexible pneumatic actuator FPA
(a) Structure of FPA
(b) Photo of FPA
1 pipe connector; 2,5 cover; 3 rubber tube; 4 helical steel wire
The working principle of FPA is as follows. Compressed air fills into the FPA by the pipe connector. Under the high pressure of compressed air inside FPA, the rubber tube will expand. Because the helical steel wire restrains its deformation in the radial direction, FPA will stretch in the axial direction. When the FPA is deflated, it will return to its original state, due to the elastoplasticity of rubber tube. The air pressure in the FPA is adjusted properly, and then the elongation of FPA can be controlled.

Based on the study of FPA, a bending joint and a side-sway joint which are driven by FPA are proposed by the author’s research team. And then a new type of air-driven multi-fingered dexterous hand, named ZJUT Hand, is developed. As shown in Fig.2 and Table.I, ZJUT hand has five fingers with 20 DOFs in total, and its size is approximately 1.5 times as large as human hand. Each fingertip is equipped with a five-component force sensor\(^\text{[14]}\). Each joint of the finger is equipped with a contactless magnetic rotary encoder AS5045 manufactured by Austriamicrosystems AG\(^\text{[15]}\).

### III. CONSTRUCTION METHOD FOR GRASPING MODEL

#### A. Hyperelliptic equation

![3D hand model and photograph of ZJUT Hand](image)

**Fig.2 Prototype of ZJUT Hand**

**TABLE I. STRUCTURAL PARAMETERS OF ZJUT HAND**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link length</td>
<td>(a_1)</td>
<td>mm</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>(a_2)</td>
<td>mm</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>(a_3)</td>
<td>mm</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>(a_4)</td>
<td>mm</td>
<td>25</td>
</tr>
<tr>
<td>Angle range of bending joint</td>
<td>(\alpha)</td>
<td>°</td>
<td>0° [0 90°]</td>
</tr>
<tr>
<td>Angle range of side-sway joint</td>
<td>(\beta)</td>
<td>°</td>
<td>-15° [15°]</td>
</tr>
<tr>
<td>Thickness of palm</td>
<td>-</td>
<td>mm</td>
<td>27</td>
</tr>
<tr>
<td>Width of palm</td>
<td>-</td>
<td>mm</td>
<td>125</td>
</tr>
<tr>
<td>Maximum height of palm</td>
<td>-</td>
<td>mm</td>
<td>135</td>
</tr>
<tr>
<td>Distance between middle fingertip and bottom of the palm</td>
<td>-</td>
<td>mm</td>
<td>245</td>
</tr>
<tr>
<td>Body Weight of ZJUT Hand</td>
<td>(m_a)</td>
<td>g</td>
<td>400</td>
</tr>
</tbody>
</table>

Hyperelliptic curve firstly proposed by French mathematician Gabriel Lame is one kind of superquadric surface. Superquadric surface is given by a quadratic equation with additive parameters, and it is convenient to change the shape of a curve or surface by adjusting the parameters. Hyperelliptic equation in Cartesian coordinates is:

\[
\left(\frac{y}{r_x}\right)^2 + \left(\frac{z}{r_y}\right)^2 = 1
\]

where \(s\) is a real number, when \(s = 1\), standard elliptic equations can be obtained.

Eq.(1) can also be expressed as follows:

\[
\begin{align*}
    y &= r_y \cos^s \omega, \quad -\pi \leq \omega \leq \pi \\
    z &= r_z \sin^s \omega
\end{align*}
\]

When \(r_y = r_z\) and taking the different values of \(s\), a set of hyperelliptic curves can be obtained. As shown in Fig.3, The characteristics of hyperelliptic curves are: the curves can simulate a lot of natural shapes only by changing the different values of \(s\), including elliptical, rectangular and other irregular shapes.

Coordinate transformation of hyperelliptic equation Eq. (2) is shown in Fig.4. The coordinate of origin \(a_1\) of coordinate system \(\{B\}\) relative to coordinate system \(\{A\}\) is \((y_o, z_o)\), and the angle between the axes of is \(\varsigma\).

According to coordinate transformation, general hyperelliptic equations can be derived

\[
^{A}P = ^{A}R \cdot ^{B}P + ^{A}P_{O_h}
\]

where

\[
^{A}R = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \varsigma & -\sin \varsigma \\ 0 & \sin \varsigma & \cos \varsigma \end{bmatrix}
\]

\[
^{B}P = \begin{bmatrix} 0 \\ r_y \cos^s \omega \\ r_z \sin^s \omega \end{bmatrix}
\]

\[
^{A}P_{O_h} = \begin{bmatrix} 0 \\ y_o \\ z_o \end{bmatrix}
\]

![Hyperelliptic curves with the different values of s](image)

**Fig.3 Hyperelliptic curves with the different values of s**
Because of the unknown target objects have uncertain shapes and quality, so it is difficult to establish the accurate model. A new construction method of grasping model for unknown target objects based Adaptive Network Based Fuzzy Inference System (ANFIS) is proposed in this paper.

IV. GRASPING MODEL IDENTIFICATION BASED ANFIS

A. ANFIS and its general structure

ANFIS introducing Fuzzy system into Neural network is an extent of network algorithm that has abilities of supervise and self-learning. Using Takagi-Sugeno fuzzy model (T-S) to approximate non-linear object model, ANFIS can obtain the optimal model parameters through multilayer adaptive neural network. ANFIS is not only able to extract language rules from experience of experts, but also can use input, output data and self-learning network function to optimize the fuzzy rules, membership functions and fuzzy decision algorithm of the fuzzy logic system. It can transform learning results of network to rules of fuzzy logic system. In other words, ANFIS gets information from the sample data, and then adjust the membership function making the model consistent with the given sample data. Due to good adaptive and self-learning features, ANFIS has very good application prospects in the field of non-linear model, and has been successfully applied in robot controller design, inverted pendulum control system and other non-linear systems.

ANFIS is a kind of neural network that is based on T-S fuzzy inference system. As shown in Fig.6, supposing a first-order T-S fuzzy system has two input variables \( x, y \) and one output variable \( z \), it has two IF-THEN rules:

\[
\begin{align*}
R_1: & \quad \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1 \\
R_2: & \quad \text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2
\end{align*}
\]

\( A_1, B_1, A_2, B_2 \) are in the input variable's fuzzy set.

![Fig.6 Reasoning process of first-order T-S fuzzy system](image1)

\[
\begin{align*}
z &= \frac{\overline{\mu}_{A_1}f_1 + \overline{\mu}_{A_2}f_2}{\overline{\mu}_{A_1} + \overline{\mu}_{A_2}}
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\end{align*}
\]
Equivalent ANFIS model of the first-order T-S fuzzy system is shown in Fig.7. It has five layers, and the role and function of each layer is as follows.

Layer 1: Fuzzification layer. The membership value of each input value can be obtained. \(O_{1,i}\) represents the i-th node output at the first layer, that is the mapping of i-th input variable into the corresponding fuzzy set. \(\mu_{A_i}\), \(\mu_{B_i}\) is the i-th membership function. Each node output at the first layer can be expressed as

\[
\begin{align*}
O_{1,i} &= \mu_{A_i}(x), & i &= 1,2 \\
O_{1,i} &= \mu_{B_{i-2}}(y), & i &= 3,4
\end{align*}
\]  
(9)

Layer 2: Rule layer. The node at this layer has a fuzzy rule. The node output represents the activity intensity of each rule. Node function can use T-operator of AND, and then each node output at the first layer, that is the mapping of i-th input variable into the corresponding fuzzy set.

\[
O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), & i &= 1,2
\]  
(10)

Layer 3: Normalization of activity intensity. Each node at this layer is marked as a fixed node \(N\). Normalized value of i-th node is the ratio of i-th activity intensity to sum of all activity intensities. The output of the third layer can be expressed as

\[
O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, & i &= 1,2
\]  
(11)

Layer 4: Output of each fuzzy rule. Each node that has a node function is an adaptive node. Output of this layer is

\[
O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)
\]

(12)

where \(\{p_i,q_i,r_i\}\) is the parameter set for i-th node.

Layer 5: Output layer. The node is marked as \(\Sigma\). The system output of ANFIS can be obtained as

\[
O_{5,i} = \sum \bar{w}_i f_i = \sum \bar{w}_i
\]

(13)

B. Equivalent rules of target objects

The target objects grasped by robot dexterous hand are always unknown, and their shape and structure are irregular and non-uniform. Establishing grasp models of all target objects not only increases the difficulty of model identification, but also greatly reduces the identification efficiency. A new method which makes a class of unilateral linear or nearly linear target objects to be equivalent to rectangular models is proposed. This method can deal with a class of unilateral linear or nearly linear objects not only increases the difficulty of model identification, and non-uniform. Establishing grasp models of all target objects always unknown, and their shape and structure are irregular and non-uniform. Establishing grasp models of all target objects not only increases the difficulty of model identification, but also greatly reduces the identification efficiency. A new method which makes a class of unilateral linear or nearly linear target objects to be equivalent to rectangular models is proposed. This method can deal with a class of the target object with the same characteristics, greatly improve the efficiency of identification and enhance the grasping real-time. The principle of this method is as follows.

Supposing five fingertips of the dexterous hand are contact with the target objects, the projection in the \(y_0z_0\)-plane of thumb base frame is shown in Fig.8. \(C_i(y_0, z_0)\) \(i = 1,2,\ldots,5\) is respectively coordinate of five contact projection point in \(y_0z_0\)-plane; \(h_i (i = 1,2,3)\) is respectively distance of projection point \(C_1\) and \(C_3\) to line \(C_2C_5\); \(h_4\) is distance between projection point \(C_2\) and \(C_3\).

\[
\begin{align*}
\begin{cases}
\frac{y_{01}}{z_{01}} + b &= \sqrt{1 + k^2} \\
\frac{y_{03}}{z_{03}} + b &= \sqrt{1 + k^2} \\
\frac{y_{04}}{z_{04}} + b &= \sqrt{1 + k^2} \\
\frac{(y_{02} - y_{05})^2 + (z_{02} - z_{05})^2}{h_4} &= \frac{y_{02} - y_{05}}{y_{02} - y_{05}} \quad \text{(14)}
\end{cases}
\end{align*}
\]

where

\[
k = \frac{y_{02} - y_{05}}{y_{02} - y_{05}} \quad \text{(15)}
\]

\[
b = \frac{z_{02} - z_{05}}{y_{02} - y_{05}} \quad \text{(16)}
\]

Given the distance \(h_i (i = 1, 2, 3)\), we define: (1) when \(h_2 = h_3 = 0\), the target projects are unilateral linear; (2) when \(h_2 \neq 0\) or \(h_3 \neq 0\), and \(\max(h_2, h_3) \leq \sigma \quad (\sigma = 5\%)\), the target projects are nearly unilateral linear. If any of the above conditions is true, this target object can be equivalent to the rectangular object and its grasp model can be established as rectangular model. As shown in Fig.9, solid line is the actual projection view of the target object, and dotted line represents the equivalent rectangular model.
C. Grasping model identification based ANFIS

Based on hyperelliptic equation and general structure of ANFIS, A new method for grasping model identification for dexterous hand based ANFIS is proposed. And its basic architecture is a five-layer network which includes five inputs (coordinates of five contact projection point in $y_0z_0$ plane) and three outputs (hyperelliptic equation parameters $r_y, r_z, s$), as shown in Fig.10. The grasping model identification process is as follows.

1. Input layer: according to the contact points between five fingertips and the target objects, the coordinates $C(y_0, z_0) (i=1, 2,..5)$ of projection point in $y_0z_0$-plane can be obtained;

2. Conversion layer: given the coordinates $C(y_0, z_0) (i=1, 2,..5)$, the corresponding distance $h_i(i=1, 2,..4)$ can be obtained;

3. Decision layer: according to the distance $h_i (i=1, 2,..4)$, the dexterous hand can determine whether the target objects are unilateral linear or nearly linear, if “Yes”, the target objects can be equivalent to the rectangular object. And then it is easy to get the parameters $r_y, r_z$.

4. ANFIS system: if the target objects are unilateral non-linear, it need to adopt ANFIS system to establish the grasping model and obtain the parameters $r_y, r_z, s$.

D. Simulation experiments for grasping model identification

It is relatively easy to establish the grasping model of unilateral linear or nearly linear target objects. Therefore, simulation experiments for grasping model identification of unilateral non-linear target objects are carried out by using ANFIS system in this section.

1. Selecting the training samples: 3D design software is used to construct the 1:1 virtual simulation system for ZJUT Hand. The different known pre-trained models of target objects are introduced into the simulation system. The constraint between each fingertip and the target object is established, and then ZJUT Hand grasps target objects with the optimal posture in the virtual system. In the virtual environment, it is easy to obtain the accurate projection coordinates in $y_0z_0$-plane of contact points which can be chosen as the training samples.

2. Determining the number of samples: The number of samples should be appropriate. Calculation of ANFIS will increase in proportion with the increase of the training samples. With the increase of training samples, neural network might not be guaranteed to converge toward the optimal direction, and the problem of over-training will emerge. Three groups of data are used in this paper. The first group of data which consists of 110 data sets is training samples. The second group of data which has 30 data sets is model calibration samples. And as the auxiliary and decision inputs of ANFIS, these data are not involved in the training, supervise the training process and avoid the model over-matching. The third group of data which has 20 data sets is model test samples. And these data are used to validate the post-training model and analyze the error.

3. Determining the simulation parameters and conditions: Input variables membership function is set to normal distribution function (gbellmf). The number of input-output fuzzy rule is set to 54. Output variables membership function is set to linear. The number of training is set to 150. The training method combines least squares with BP network algorithm.

4. Simulation results and model validation: The simulation experimental results are shown in Fig.11. The training errors of parameters $r_y, r_z, s$ are shown in Fig.11 (a), Fig.11 (c) and Fig.11 (e). It is concluded from the results that the training absolute errors of $r_y, r_z$ are within $\pm 0.002$ mm, the training absolute error of $s$ is within $\pm 8 \times 10^{-5}$, and the maximum relative errors of $r_y, r_z, s$ are all less than 0.01%. The validation results of test samples for post-training model are shown in Fig.11(b), Fig.11(d) and Fig.11(f). Where, “×” is test sample data; “.” is output of the post-training model; the average errors of $r_y, r_z, s$ between test samples and outputs of the post-training model are respectively 1.719mm, 1.640mm and 0.0157. Simulation experimental results show that the grasping model reconstruction method based on ANFIS can establish the model of the target objects, and has very good recognition accuracy and convergence.

![Fig.10 Structure of grasping model for dexterous hand based on ANFIS](image-url)
Precision grasp for robot multi-fingered dexterous hand mainly includes two aspects of contents: (1) Constructing grasp model of target object; (2) Choosing a reasonable number of fingers for grasping and position of contact points; Performing stable grasping of the objects and completing the grasping force optimization. Grasp planning experiments for ZJUT Hand have mainly studied the problem (1) in this paper.

A. Experimental system

The schematic diagram of grasp planning experimental system for ZJUT hand is shown in Fig.12. IPC sends 22-channel analog voltage signals by D/A converters which can adjust output air pressure of 22 electro-pneumatic regulators (SMC: ITV0050-3BS) connected with FPAs of the ZJUT Hand’s joints. Under the air pressure, the joints of the ZJUT Hand will output bending angle and torque. At the same time, the pressure inside FPAs feeds back to the IPC via the pressure sensor in the electro-pneumatic regulator by A/D converters. The Joint angles and the fingertip force are respectively measured by the AS5045 and the five-component force/torque sensor. All real-time sensor information is sent to IPC via the DS pic embedded microprocessor by CAN bus. Combining Delphi and the MATLAB, the PC control and graphics display software are developed.
B. Experimental results

Structure parameters of two general target objects (I, II) are shown in Table II. As shown in Fig.15, ZJUT Hand respectively grasps two target objects with the optimal posture. According to the feedback information of fingertips’ five-component force/torque sensors, it can judge whether the fingertips contact with the target objects. When five fingertips have contacted with the target objects, all the joint angles measured by AS5045 will feed back to the IPC. And then each projection distance $h_i$ ($i = 1, 2, 4$) in $y_0z_0$-plane can be calculated. According to the distance $h_i$ ($i = 1, 2, 4$), it can determine whether the target objects are unilateral linear or nearly linear, if “No”, it need to adopt ANFIS system to establish the grasping model and obtain the parameters $r_x$, $r_y$, $s$. The experimental results show that: the target object I can be equivalent to the rectangular object, the projection of all the contact points between the fingertips and the target object II in the $y_0z_0$-plane is nearly circular, and then contraction parameters $r_x$, $r_y$, $s$ of target object II are shown in Table II.

<table>
<thead>
<tr>
<th>Table II. STRUCTURE PARAMETERS OF TWO TARGET OBJECTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>I</td>
</tr>
<tr>
<td>II</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

(1) A new method for grasping model identification based ANFIS is proposed.

(2) New equivalent rules of target objects are proposed and greatly improve the efficiency of identification.

(3) Simulation experiments are completed. Simulation experimental results show that the method can easily establish the model of the target objects, and has very good recognition accuracy and convergence.

(4) The grasp planning experiments are carried out. Experimental results show that ZJUT Hand is able to construct the models of typical target objects.

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REFERENCES


