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Automatic Assembly Task of Electric Line Using 6-Link Electro-Hydraulic Manipulators

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Uninterrupted power supply has become indispensable during the maintenance task of active electric power lines as a result of today's highly information-oriented society and increasing demand of electric utilities. The maintenance task has the risk of electric shock and the danger of falling from high place. Therefore it is necessary to realize an autonomous robot system using electro-hydraulic manipulator because hydraulic manipulators have the advantage of electric insulation. Meanwhile it is relatively difficult to realize autonomous assembly tasks particularly in the case of manipulating flexible objects such as electric lines. In this report, a discrete event control system is introduced for automatic assembly task of electric lines into sleeves as one of the typical task of active electric power lines. In the implementation of a discrete event control system, LVQNN (linear vector quantization neural network) is applied to the insertion task of electric lines to sleeves. In order to apply these proposed control system to the unknown environment, virtual learning data for LVQNN is generated by fuzzy inference. By the experimental results of two types of electric lines and sleeves, these proposed discrete event control and neural network learning algorithm are confirmed very effective to the insertion tasks of electric lines to sleeves as a typical task of active electric power maintenance tasks.

Key Words : Fluid Power Systems, Automatic Assembly, Neural Network, Electric Line, Manipulator

1. Introduction

As a consequence of today's highly information-oriented society and increasing demand of electricity, uninterrupted power supply has become indispensable for most electric utilities. Outage-free maintenance techniques for overhead distribution power lines have been developed and used recently by several companies in order to fulfill this requirement (Boyer, 1996, Takaoka ; Takaoka, 2001).

In the conventional maintenance techniques, workers have to do their job on a live electric power line, indirectly with various kinds of insulated hot-sticks or directly touching the line with rubber gloves from an insulated bucket. Therefore, work is performed in a hazardous environment with both the risk of electrical shock and the danger of falling from a high place. In addition, workers have to be very skilled and have to work cooperatively under very demanding tasks. In the near future, it is anticipated to develop autonomous manipulator system where man is not necessary in the maintenance task. For this purpose, an electro-hydraulic manipulator for the maintenance task of active electric power lines has been developed to realize the maintenance task autonomously (Yamamoto, 1995). This paper deals with the task of inserting flexible electric lines to sleeves among the typical tasks in the maintenance of active power electric lines.

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In previous studies, Hirai (1994) showed that the buckling shape of a flexible beam is calculated by minimizing the potential energy of the beam, and the shape is also affected by gravity and torsion of the beam. Zheng (1991) proposed that the insertion path should be aligned with the bending shape of the beam if friction at the insertion point is negligible. However, the beam buckles and cannot be inserted by correcting the insertion path. Inoue (1985) developed a hand-eye system to insert a rope into a hole. In their system, the insertion is performed by measuring the center of the tip of the rope using stereo vision, and finding the relative position between the center of the rope and the hole. Chen (1992) proposed a method of measuring the characteristics of a beam by a vision sensor. They showed that the flexural rigidity of the beam can be calculated from the shape of the beam. However, they assumed that one end of the beam is fixed and the other is free, so this model does not apply to a beam on which a force acts. Byun (1994) proposed a method of measuring the shape of flexile object by stereo vision. Since the method can only measure the shape of the wire, it cannot determine the force acting on the wire. Wakamatsu (1995) proposed a method of calculating the shape of linear objects by minimizing the potential energy of the object, but the method requires measuring the position and the direction of both sides of the wire correctly, and the calculation is very time-consuming.

In this paper, we propose a new method of inserting a flexible electric line into a sleeve by linear vector quantization neural network, which plays the role of modifying the discrete event of insertion task. In this research, we assume that the tip position of electric line is already known and the electric line contacts with the sleeve in the initial stage of assembly task, and we focus on the assembly task during contact condition, not the recognition of tip position of electric line.

In Section 2, the dual arm manipulator system and two types of electric line and sleeve used in this experiment are explained. In section 3, linear Vector Quantization Neural Network (which is abbreviated as LVQNN) is introduced and the acquisition of learning data for LVQNN is explained. In section 4, the experimental results of inserting the electric lines into sleeves are shown, and data generation for fuzzy rule is explained in section 5.

2. Experimental Apparatus

The schematic diagram of this manipulator system is shown in Fig. 1. The supply pressure to this system is 10 MPa. Each control algorithm is calculated at the sampling rate of 1 kHz by using microcomputer (NEC PC-9821V20, Pentium (200 MHz)) and the calculated command input controls the servo valves (Tokyo Seimitsu Sokki, 401F-110, Bandwidth : 120 Hz) by servo amplifiers (Tokyo Seimitsu Sokki, SA-201) through 12-bit D/A board (CONTEC, DA12-16). The rotational angle of each axis is calculated using rotary encoder (Canon, R-10), which is the input to the computer through the Up/Down Counter (Micro-Science, UPC-4298XPC). The resolution of each axis is 0.044°. The force sensor (Nitta, USF-4520A-150) is installed in the top position of 6-link electro-hydraulic manipulator shown in Fig. 2 and the force is measured using 12-bit A/D board (Micro Science ADM1498 BPC). In the maintenance task of real active

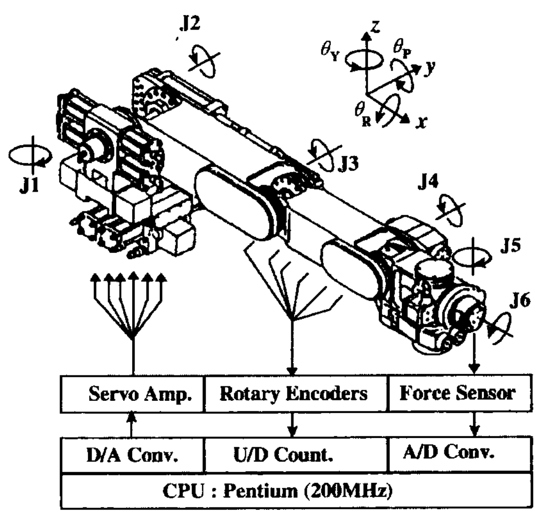


Fig. 1 System configuration of 6-link electro-hydraulic manipulator

power electric line, a dual arm 6-link manipulator system is used to perform the insertion task of manipulator in the left side is grasping the electric line and that of right manipulator is grasping the sleeve shown in Fig. 3. In the real maintenance task, there are 16 kinds of electric lines and sleeves but two types of electric lines and sleeves are used here, which is shown in Fig. 4. The outer diameters of Type A and B electric lines are 18 and 14 mm respectively and only of an electric line to the sleeve. The end effector Type A electric line is utilized in the learning of neural network. The clearance of each electric line and sleeve is 1 mm.

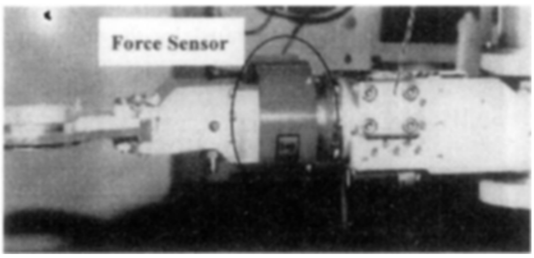


Fig. 2 Installation of Force sensor

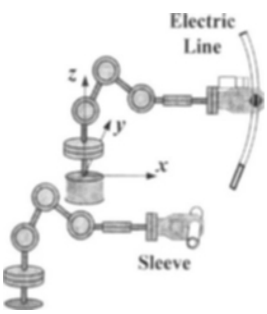


Fig. 3 Insertion task of electric line to sleeve

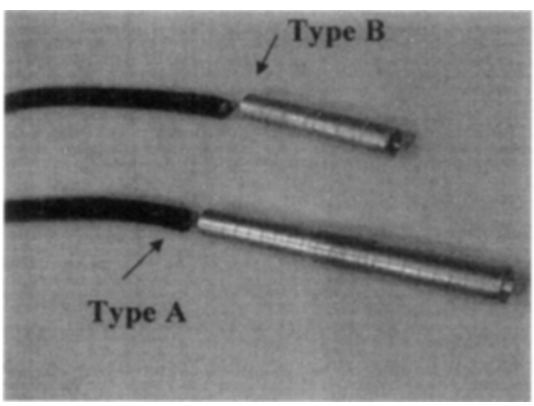


Fig. 4 Two Types of Electric Lines and Sleeves

3. Proposition of Neural Network Learning of Discrete Event

3.1 Discrete event control system

Insertion task of electric line into sleeve, which is the target task in this paper, is very difficult to realize because the stiffness and the bending shapes are very different depending on the electric lines. In this research, it is assumed that the end point of electric line is already known and the end points of electric lines contact with sleeve in the initial insertion stage. However it is not possible to realize the insertion task only by simple trajectory planning. As a possible solution to realize this task, a discrete event control system is newly introduced, as shown in Fig. 5 where x_r, x_d, x_c, u, θ and f describe the reference trajectory, the output of discrete event controller, modified trajectory, control input, rotation angle of each axis and the contact force to the environment, respectively. The discrete event control system here plays the role of recognizing the contact status between electric lines and sleeves from the contact force and adjusting the reference trajectory and attitude of manipulator properly. The dual arm manipulator is controlled by one discrete event controller. Here we use impedance control system proposed by Ahn (1999) as the continuous controller. Many theories such as Petri-net (McCarragher, 1995) and so on, have been proposed in order to realize the discrete event control system, but the accurate recognition of the contact state of flexible objects like electric

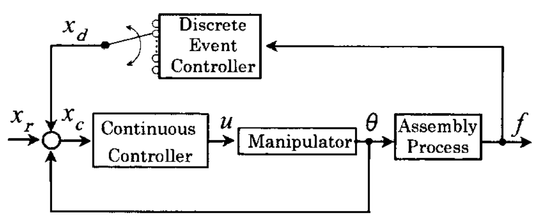


Fig. 5 Discrete Event Control System

line is very difficult because of the flexibility of contact objects. In this paper, Learning Vector Quantization Neural Network (LVQNN), (Kohonen, 1987) is applied to the insertion task of electric lines with sleeves.

The characteristics of the proposed control algorithm are as follows.

- The insertion task can be realized only if the minimum learning data is prepared with respect to the possible position and attitude between electric line and sleeve.
- It takes little computation time in the implementation of LVQNN and the structure of control algorithm is very simple in the real implementation of insertion task.

This learning method is also applicable to the insertion task of resembling electric lines and sleeves if the learning of LVQNN is completed with respect to the typical electric line and sleeve.

Next, the leaning method of Discrete Event using LVQNN is explained.

3.2 Learning of discrete event using LVQNN

In the insertion task of electric lines into sleeves, it is quite difficult to calculate the contact state from the contact force on tip of manipulator by the force sensor, because the electric line is very flexible and easy to bend. Here we apply LVQNN as a means of supervisor of discrete event, which functions here as the classification of 18 cases of contact states. Figure 6 shows the architecture of LVQNN, where P, y, W_1, W_2, R, S_1, S_2 and T denote input vector, output vector, weight of competitive layer, weight of linear layer, the number of neuron of input layer, competitive layer, linear layer and target layer, respectively. The proposed LVQNN is a supervised learning algorithm and is composed of 2 layers. The first is the competitive layer with 12 neurons (S1) and functions learning of classification of input vector. And the second is linear layer with 18 neurons (S2) and classifies the competitive layer according to the designer's intention. For the generation of learning data, human probes the electric line into sleeve, which is explained in detail in next section. In the learning process, the weight of LVQNN is updated by the following Kohonen (Kohonen, 1987) learning rule.

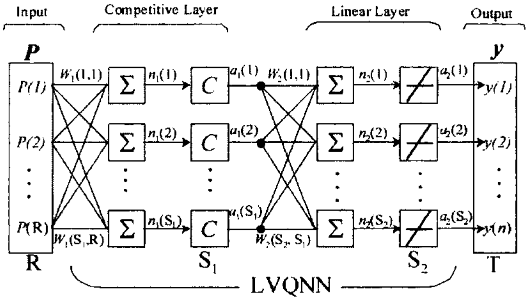


Fig. 6 Architecture of LVQNN

$$\Delta W_1(i, j) = \lambda \cdot a_1(i) \cdot (p(j) - W_1(i, j)) \quad (1)$$

where λ is the learning ratio and $a_1(i)$ is the output of competitive layer.

3.3 Learning data generation by human probing and learning of LVQNN

In this section, the generation method of learning data for LVQNN is explained. The total structure of LVQNN with input and output data is shown in Fig. 7. The input data for LVQNN are forces in the direction of x, y, z axis (see the reference coordinates in Fig. 1) and moments in the direction of x and z axis, where the moment in the direction of y axis is excluded because the electric lines rotate freely with respect to sleeves and have little information in the recognition of contact state. The output from LVQNN is a class among 18 discrete classifications, where 18 cases are composed of the combination of the movements of electric line in the direction of x, z axis (D_x, D_z) and the rotation of sleeve (D_φ) with respect to x axis. The learning data for LVQNN is measured by human's probing of electric lines and sleeves. During experiments for acquisition of learning data, sleeve is fixed by left manipulator and the electric line is moved in the y direction with the speed of -0.01 m/s by human. At the same time, the center position of electric line is adjusted in the x and z direction with plus, zero or minus value, respectively by the movement of human's hand. In each experiment, roll attitude of sleeve is fixed with plus or minus

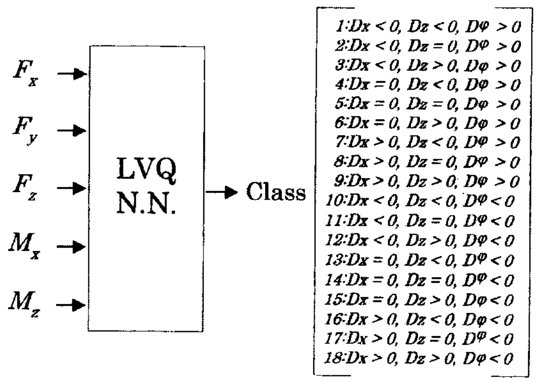


Fig. 7 Learning Data for LVQNN

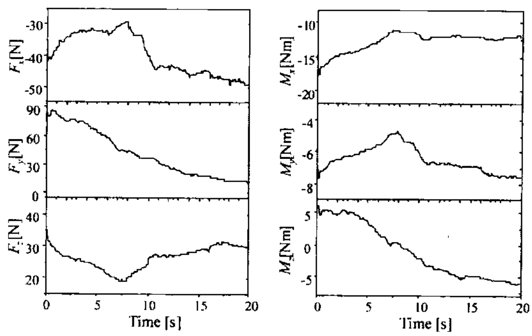


Fig. 8 One Sample of Learning Data (Class 7)

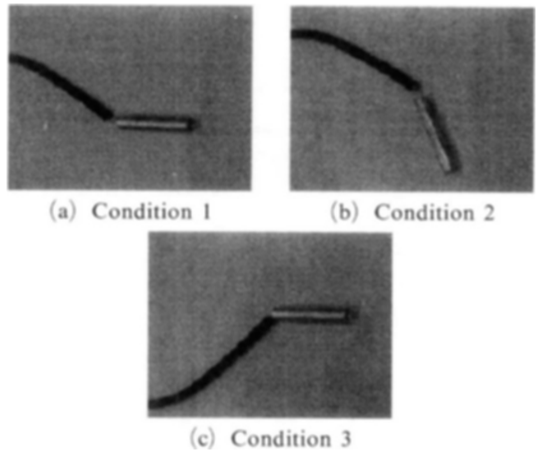
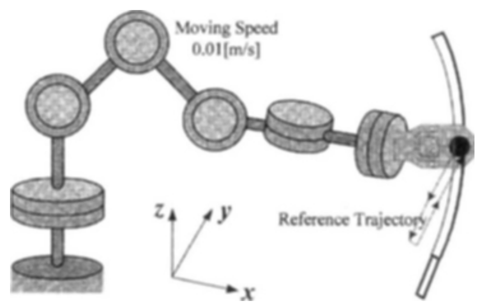


Fig. 9 Initial Attitude between Electric Line and Sleeve



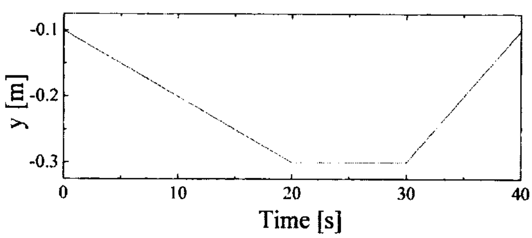


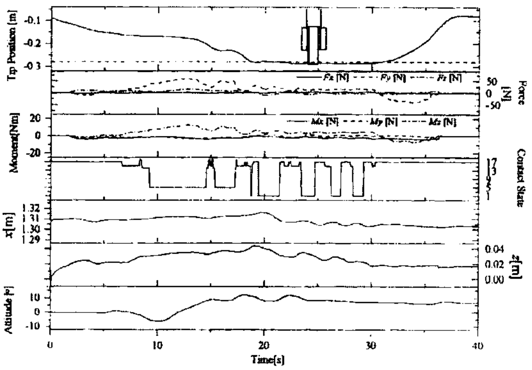
Fig. 10 Reference Trajectory

value. Therefore total 18 cases of experiments are carried out to prepare for the learning data of LVQNN. One typical measured force and moment using TYPE A electric line are shown in Fig. 8, which corresponds to the class 7 in Fig. 7. The experiment time is 20 seconds and the learning of LVQNN is performed before the insertion task is executed. The total set of training data is 5400.

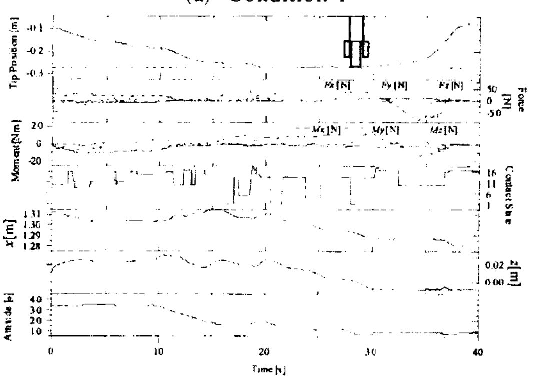
In the learning stage of LVQNN, the number of neurons of competitive layer is set to 30 and the learning rate is 0.01. Matlab Function trainlvq (Beale, 1994) is used in the learning stage. Experimental results are shown in the next section.

4. Experiment of Insertion Task of Type A Electric Line and Sleeve

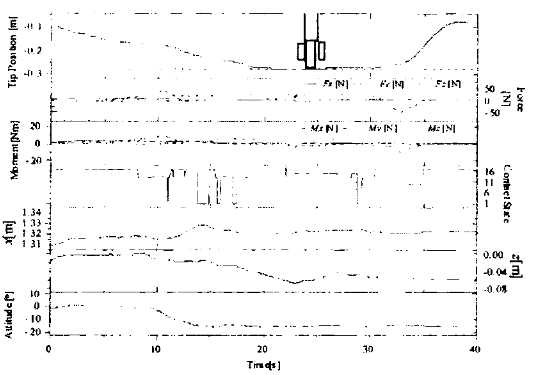
In this section, insertion tasks are performed with type A electric line and sleeve. To consider the real work in the field, experiments are done under 3 different cases as shown in Fig. 9. To realize the insertion task, the reference trajectory of the left manipulator is set as shown in Fig. 10. The experimental results are shown in Figs. 11 (a) ~ (c), which correspond to the case of condition 1, 2 and 3 in Fig. 9 respectively. In each figure, the tip position of manipulator for electric line, the contact force, moment and the output of LVQNN are shown respectively. The contact state, which is the discrete output of LVQNN, is



(a) Condition 1



(b) Condition 2



(c) Condition 3

Fig. 11 Experimental Results of Type A Electric Line

shown in the middle of each figure. The displacement of the center position of electric line and the attitude of sleeve are shown in the bettom of each figure. In the top of each figure, the insertion task can be said to be completed if the tip position of electric line (solid line) reaches the end point of sleeve (dashed line). Therefore it is understood that the insertion task of electric line to sleeve is

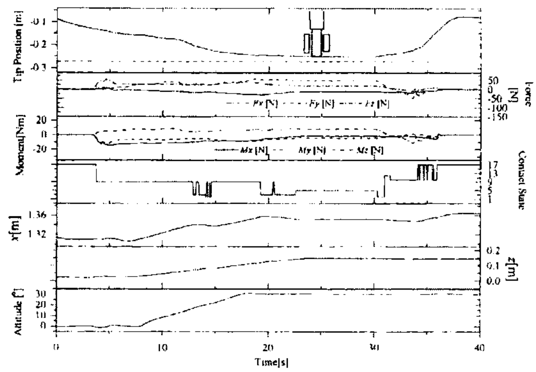


Fig. 12 Experimental Results of Type B Electric Line

realized regardless to the 3 initial attitude conditions. However, the experiment using the Type B electric line and sleeve cannot be realized which is shown in Fig. 12. This is because the force and moment are not with the same magnitude in the case of different type of electric line and sleeve. Therefore it is concluded that the learning data is insufficient in the learning of LVQNN. In the next section, a novel method to generate learning data by fuzzy algorithm is proposed.

5. Data Generation by Fuzzy Inference

In the real active power electric line work, approximately 16 kinds of electric lines and sleeves are used. Therefore it is time-consuming to obtain LVQNN learning data of all kinds of electric lines and sleeves only by experiment. By this reason, learning data generation algorithm by fuzzy rule is proposed to realize the insertion task of electric lines and sleeves which are not used in the learning stage of LVQNN. The only assumption of this learning data generation is that even if the magnitude of force changes with respect to various electric lines and sleeves, the force ratios are not changed. The learning data generation algorithm, which is based on the fuzzy rule, is shown in Fig. 13. The forces and moments are measured under 18 contact conditions (refer to Fig. 7) in only one type of electric line and sleeve. Next, fuzzy rule is applied to generate virtual learning data for LVQNN. Fuzzy inference is used to generate input and output training vectors for LVQNN, where the output vector (x, z, roll) is converted to class number between 1 and 18. The membership function of fuzzy rule is designed using measured force and moment data.

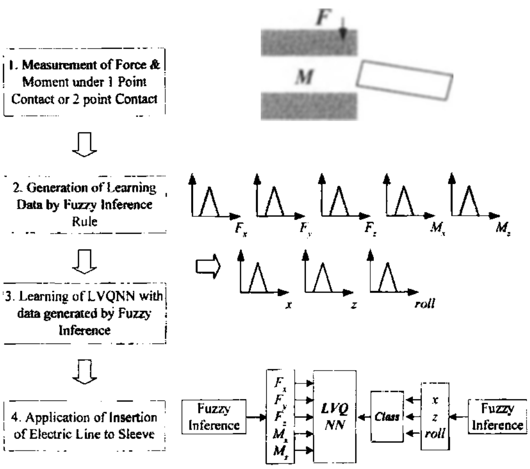


Fig. 13 Algorithm for Data Generation for Learning

Finally, using the measured data and virtual learning data by fuzzy rule, the LVQNN is trained off-line. As the inference method of fuzzy rule, Product-Max algorithm by Larsen (Lofti, 1996) is applied. One typical example of fuzzy rule is shown in Fig. 14. Figure 14 corresponds to the case 7 in Fig. 7. The experimental results of type B electric line using LVQNN trained by virtual learning data, are shown in Fig. 15(a) ~ (c). From the experimental results, it is understood that the insertion tasks of electric lines into sleeves are realized without experiments for learning data of LVQNN. The real insertion task is shown in Fig. 16. The initial attitude of dual arm manipulator is shown in Fig. 16(a). In the initial stage of insertion task, the end points of electric line and sleeve are in contact by human hand (Fig. 16(b)). During the insertion task, the reference trajectory is designed to make the manipulator with electric line is to move in the $-y$ direction (towards the manipulator with sleeve).

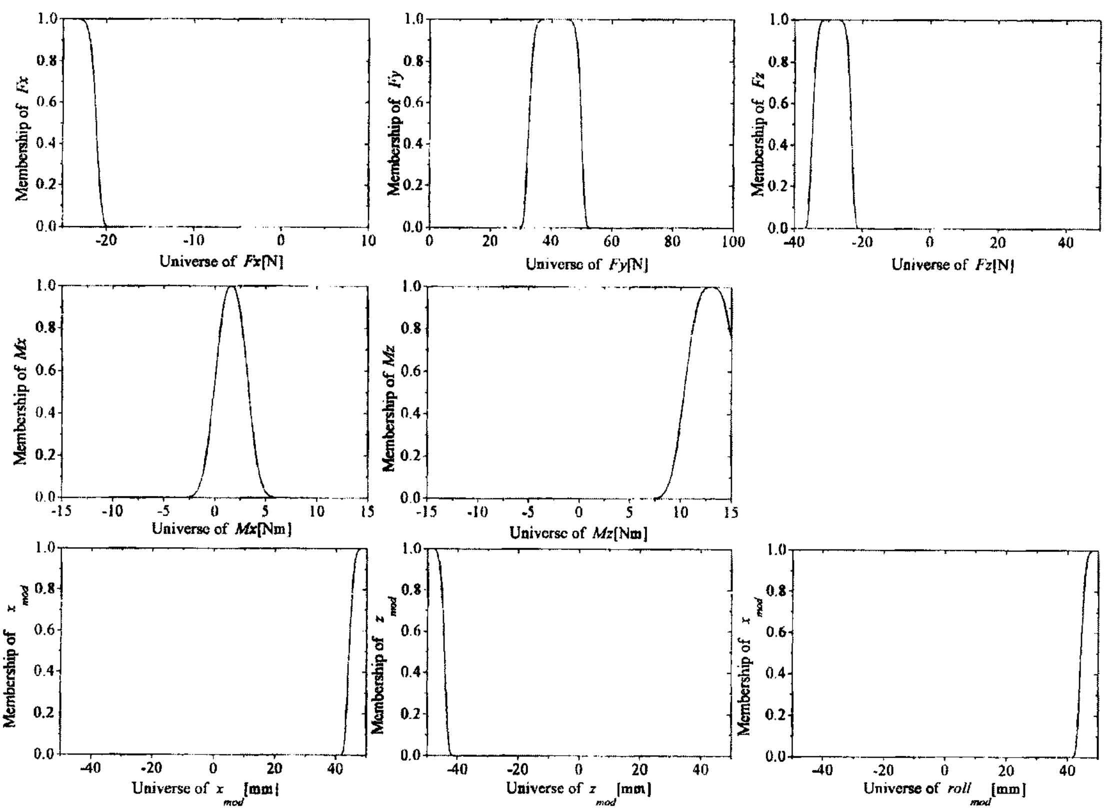
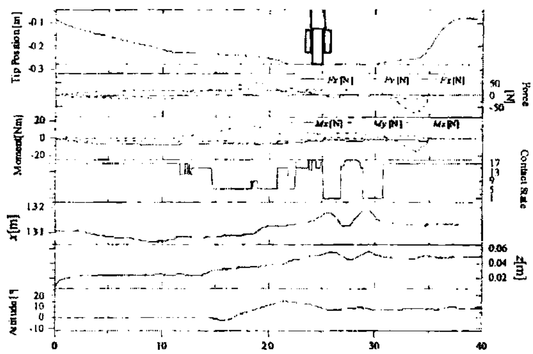
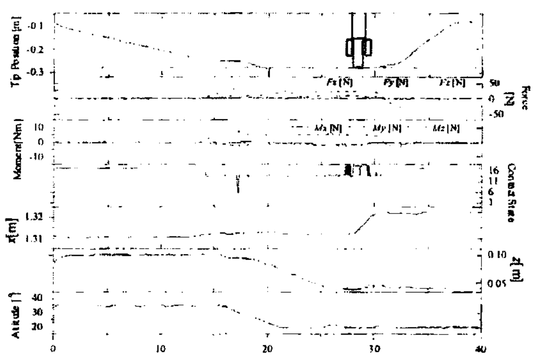


Fig. 14 One Example of Membership Function

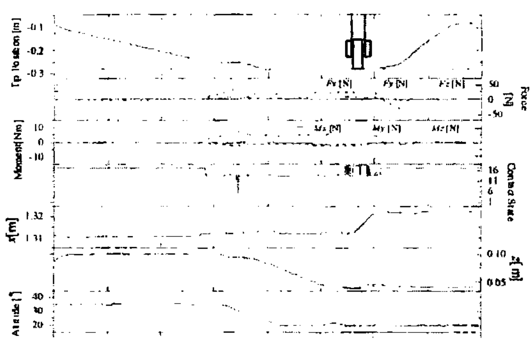
At the same time, the center position of the manipulator with electric line is adjusted by x or z direction according to the result of LVQNN, and the attitude of the manipulator with sleeve is also adjusted by positive roll direction, which is shown in Fig. 16(c). The complete insertion task is shown in Fig. 16(d), which verifies the effectiveness of the proposed algorithm.



(a) Condition 1



(b) Condition 2



(c) Condition 3

Fig. 15 Experimental Results of Type B Electric Line

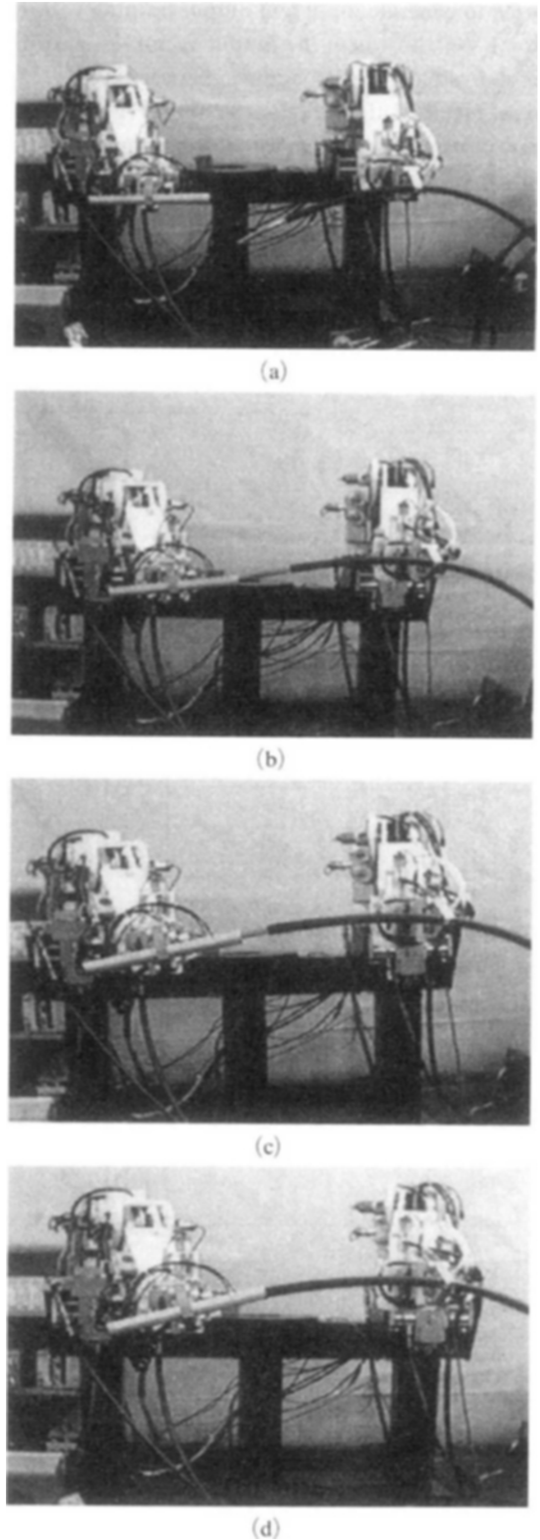


Fig. 16 Insertion Task of Electric Line to Sleeve

6. Conclusions

In this paper, a new learning method of the discrete event by linear vector quantization neural network is proposed in order to realize the inserting task of electric lines into sleeves using dual arm manipulator system. And an imaginary learning data generation method by fuzzy rule is proposed to realize electric lines and sleeves, which are not used even in the learning stage. Finally these proposed algorithms are proved to be very effective in the insertion task of electric lines into sleeves by experiments.

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