Intelligent Fusion Method Based on BP Neural Network for Robot Suit Pressure Sensing Array Data

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Abstract: *In order to eliminate the crosstalk influence existed among temperature, voltage fluctuation and sensor signal of robot tactile sensor array unit, the paper presented a sort of information fusion method in large scale sensor array based on BP neural network. By means of learning training with weight for neural network, the method can effectively eliminate the crosstalk influence for output characteristics of pressure sensing array sensor among non-target parameters and large scale sensor signals such as the environment temperature, voltage disturbance and so on, and thereby it improves the stability and reliability of robot tactile sensing suit system. Laboratory tests demonstrated that the error of the suit pressure sensor array data is less than 5%. The experimental results show that the intelligent fusion method presented in this paper can be accepted in engineering application, and the method is be propitious to improve intelligent judgment and information utilization ratio of robot system.*

Keywords: *Robot tactile, Sensing neural network, Robot tactile, Sensor array, Intelligent fusion, Data processing.*

Introduction

Robot tactile principle is based on the contact or interaction between tactile sensor and recognized object so as to complete perception of surface features and physical properties of recognized objects [6]. Robot tactile sensing suit is the tactile sensor which is distributed in the robot body, and according to the robot's shape, it can makes the cutting and sewing and wear on the robot body to perceive its environment information [11]. Its main feature is that it is in large tactile surface flexibility, and the sensor shape is not restricted and the feeling owns multi-functionality. Robot tactile sensing suit has the following characteristics:

1) The data acquired by sensor such as position, pressure, etc., are represented as two-dimensional plane information in the space.
2) Similar to machine vision, the robot tactile sensing is a passive tactile sensing, and it can obtain the time and space distribution of pressure data by means of image processing method.
3) The tactile information owns diversity [2].

In addition to spatial data, pressure distribution data, the robot can acquire a variety of physical information of the object through tactile sensor, such as the surface roughness, temperature, hardness, material quality and so on. Robot tactile sensing suit is similar to human skin function, and it can realize richer robot’s perception for the environment so as to be propitious to interaction of human-computer information. In robot tactile sensing array system, the environmental information provided by each sensor signal source has some degree of uncertainty, and in essence, it is a reasoning process about uncertainty information for the fusion process of the uncertain information [3]. The neural network can identify the classification criteria in terms of the similarity of the accepted current system sample, the method is mainly represented in the weight distribution of the network, and at the same time, it can also be used to acquire knowledge by using neural network so as to get the uncertainty reasoning mechanism [5].

System configuration and architecture

Research projects in the conductive rubber are Tianjin, Nexans conductive rubber Co., Ltd. Developed out of conductive material. The material is silicone grease rubber (Polt-siloxane elastomer) as the substrate to carbon black as conductive particles, also joined the red ocher (Fe_2O_3) and silica (SiO_2) and the antioxidant, accelerator, softener and other additives, coated with gray and black carbon particles form a thin layer of a thickness of about 0.7 mm. Research in the project to the company customized the three different levels of conductive carbon black rubber, carbon black content ratio of 5%, 10% and 15%. The conductive rubber key features are: when the applied external force on it, the resistance will rise and fall with the force, has a good piezoresistive properties; the other hand if applied external force, may be regarded as insulators. Now three kinds of conductive rubber material are made into a thin round cake as the same size structure as shown in Fig. 1, each sensor cell diameter 7 mm, thickness 0.7 mm.

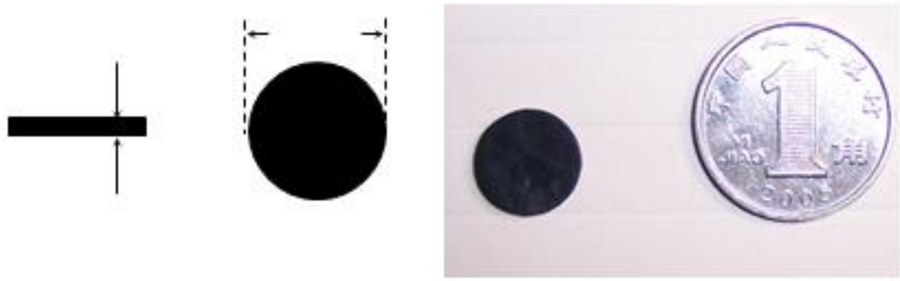

Fig. 1 Sensor cell for pressure conductive rubber

Tactile pressure sensor array is a new type of tactile sensor array, providing reliable and accurate touch-sensitive information [4]. According to their spatial resolution, sensitivity, sensitive element, stability and other requirements of the different sensing principle can be appropriate and sensitive material, which is especially important for large area array sensors, sensitive material should have good flexibility [1]. Smart clothes to cut production due to the array of clothing structure, flexible higher, so select a good flexible conductive rubber as sensitive materials [12]. Block through the production of clothing materials, components, and then connect with the combination method of sewing clothes, and ultimately cut into the robot tactile sensing can be dressed in costume.

The 8×8 matrix touch material components: the electrodes parallel to each other constitute the sensitive elements of the external leads, the (row) electrode and the lower (column) electrode perpendicular to the piezoresistive sensitive material in the middle, upper and lower electrodes is defined as the intersection of a sensitive tactile array unit, shown in Fig. 2 and Fig. 3. Tactile sensor array, the ranks of the electrode structure, its purpose are to reduce the sensor's external leads, to increase the stability and accuracy of the array [14].

The functional block diagram of basic system architecture is shown in Fig. 4. The overall system is divided into function units that are as follows:

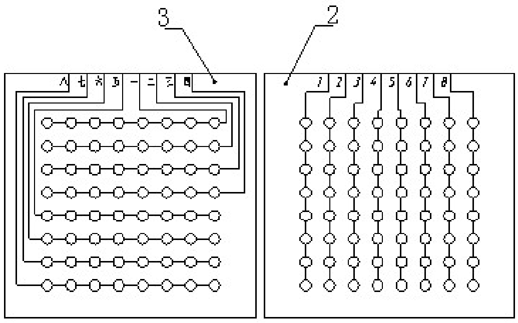

Fig. 2 Top and bottom electrodes tactile sensor array

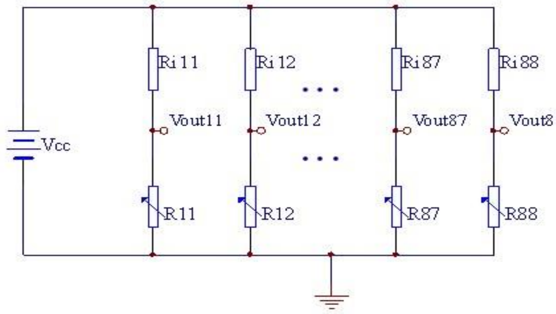

Fig. 3 Sensor array circuit

1) Data Acquisition Unit, to acquire and store the raw tactile sensor information for later retrieval.

2) Data Pre-Processing Unit, determined by the current phase. Only appropriate sensor data is transferred to the arithmetic processing unit and converted raw sensor data into the needed data formats.

3) The Compensation Unit, to be known to give data that deviate from the actual values by a known relationship.

4) The Data Processing Unit, to fuse all appropriate sensor data into a coherent data unit.

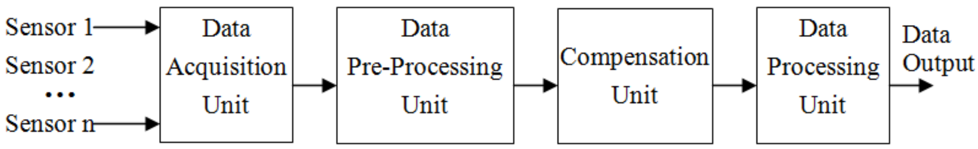

Fig. 4 Block diagram of system configuration

Information fusion strategy of tactile sensing array based on neural network

Information fusion model is the key to realize the signal processing of tactile sensing array, and it's quite difficult to establish the precise mathematical model of the relation among the sensing array and the temperature, pressure and time series by using conventional mathematical methods [10]. In tactile sensing technology, the computational intelligence information fusion is a kind of comprehensive simulation of the human brain processing complex problem [13]. Neural network as a universal function approximation, it can approach any nonlinear function of L_2 norm through the training of a large number of input / output data. The following takes the Peaks function built in MATLAB as an example to verify the nonlinear function approximation ability of neural network, and the Peaks function is shown as follows:

$$z = 3\cdot(1-x)^2 \cdot e^{-[x^2+(y+1)^2]} - 10\cdot\left(\frac{1}{5}x - x^3 - y^5\right)\cdot e^{-(x^2+y^2)} - \frac{1}{3}\cdot e^{-[(x+1)^2+y^2]} \tag{1}$$

On X, Y axis, it respectively takes the data [-3: 0.1: 3] to constitute 61×61 = 3721 pairs of training data [xp, yp, zp], and here it takes p = 1, 2, …, 3721. The neural network selects the 2-5-1 structure as shown in Fig. 5. Hidden layer neurons are the asymmetric sigmoid functions, and the output layer is the Purelin linear function, and the training algorithm selects the Traindx neural network toolbox of MATLAB neural network. The Fig. 6 is a neural network fitting of the error surface. The number of training end steps is 10000, and the training error stopping condition is as follows:

$$E = \frac{1}{P}\sum_{i=1}^{P} e_i^2 \le \varepsilon = 0.001 \qquad (2)$$

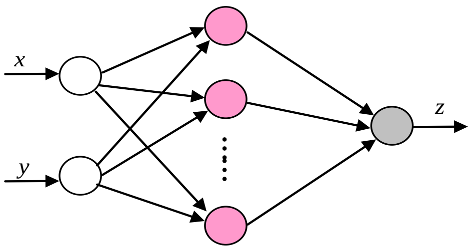

Fig. 5 Neural network structure

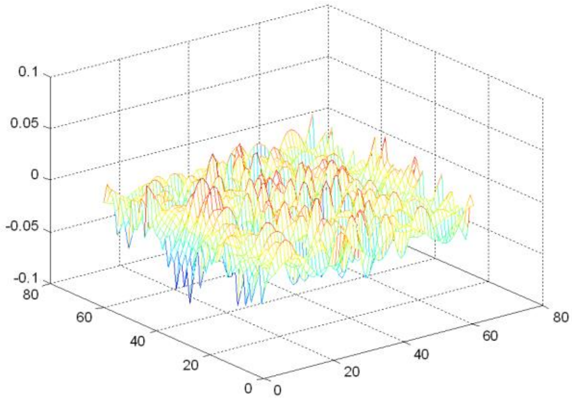

Fig. 6 Neural network error curve fitting

From the above example, it can be seen that the neural network as a universal function approximation is entirely feasible to use it as a tool for information fusion in robot tactile sensing suit. Because the sensing array output signal of robot sensing suit is the parallel distributed signal of a large area, and by general signal processing method, it is large in calculation and long in processing time. The neural network has a high degree of parallel processing capability, fault tolerance and adaptive and self-organizing management capabilities, the data acquisition card will be collected to the tactile array signal as the input of neural network, and with neural network training, it can establish a certain sort of nonlinear mapping relationship among the neural network output mode, the information of pressure distribution and stress state etc. on tactile sensing array for robot sensing suit, so the signal of the sensor array can be intelligent processing.

The sensing unit of tactile sensing array mainly exists in cross sensitivity of temperature, power fluctuation and signal crosstalk between sensing units, and the neural network can be used to carry out the information fusion of the tactile sensing array signal processing. In order to make a more precise test and estimate for the pressure distribution and the stress state of the sensing unit of the sensing array in the robot sensing suit, the pressure signal and temperature signal can be collected by the sensing array to fuse the information on the computer so as to meet the requirements of tactile sensing test accuracy. The information fusion system based on neural network for robot tactile sensing is composed of two parts of robot tactile sensing array and neural network, and the information fusion system structure is shown as in Fig. 7.

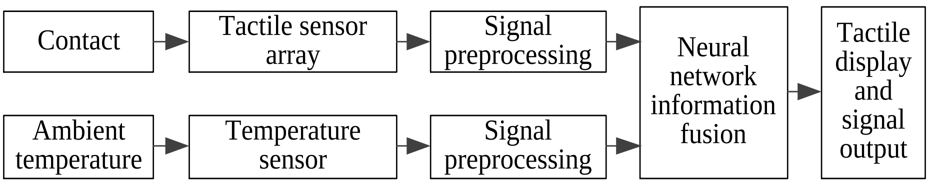

Fig. 7 Information fusion system of tactile sensing array based on neural network

The information fusion model of tactile sensing array is established by neural network.

First, a large number of input/output data is used for training, and the training sample of neural network is provided by three-dimensional calibration experimental data of the temperature, pressure and the output voltage of the sensor. Then the neural network weights are trained by the neural network with the experimental data of three-dimensional calibration, the obtained neural network weights are directly used in the subprogram of information fusion of the robot sensing suit, and carry out various levels of information fusion. The fusion processing of neural network can be realized on the each level of information fusion in robot sensing suit, and it not only signal processing can be used for signal processing of tactile sensing unit to improve the testing precision of the sensing unit, but it also be used for determining the image pattern recognition and tactile classification of tactile sensing pressure distributions and tactile images to improve the overall test performance of the sensing array. It still can make the feature extraction of multi-sensing array for robot sensing suit, and conduct the intelligent judgment, such as the high level posture and the threat assessment etc.

In the information fusion of neural network in tactile sensing array signal, the fusion process is starting from the construction of the training sample set. Each training sample mode is composed of all the sensing data of the sensor array, and namely it contains the information of all the sensors and takes the representation form of the combination through the input vector. Neural network in training and learning process makes comprehensive application of sensing array information obtain the effective classification of tactile information, and the training result is stored in the network connection weights in distribution form, so the neural network has the ability to classify the tactile sensing array signal. From neural network input to output mapping relations, it can be seen that the sensing array of a pattern of test data together constitutes a fusion input sample mode. When the input sample concentration of the fusion sample is more typical, the more comprehensive, the generalization’s ability of the network would be stronger. So in the construction of the information fusion system of neural network, the construction of the training sample is the key to complete the information fusion correctly.

Neural network modeling of tactile sensing array

According to the previous analysis conclusion of the fusion strategy selection, by means of a large number of input and output experimental data, the neural network can be trained, and finally, the task of fitting tactile pattern is realized. The selection of neural network structure is often related to the specific application of the object [15], there is no mature theory and technology currently, and at present, the most widely used is a multilayer feed-forward network [19]. In the information fusion of robot tactile sensing array based on neural network, it is adopted by the typical three-layer BP neural network, and its topological structure is shown as in Fig. 8. The three- layer BP network is divided into three layers, which are input layer, hidden layer and output layer [9]. The input layer has n nodes, the corresponding network has n input, and it takes the sensor array signal and ambient temperature signal as the input signal of the neural network [8]. The same layer nodes have no correlation, and the different-layer nodes adopt forward-connection [16].

The back propagation (BP) learning algorithm is a typical error correction method, and it is the application of gradient descent method in multi-layer feed-forward network. In the two layer feed-forward network, the hidden layer and the output layer are contained, and the research shows that the hidden layer in two-layer feed-forward network generally adopts the asymmetric S-type transfer function, and at the same time, the output layer also uses the asymmetric S-type transfer function. As long as the hidden layer contains enough neurons, the higher accuracy can be achieved so as to approach any objective function [17]. So it can use the hidden layer and output layer as the two-layer feed-forward network of asymmetric S-type transmission function [7]. It takes the signal of pressure and ambient temperature of the tactile sensing array as the inputs of the neural network, by means of BP neural network algorithm it determines the stress area of the robot's sensing array, and then in this area it respectively makes fine positioning and judges the stress size.

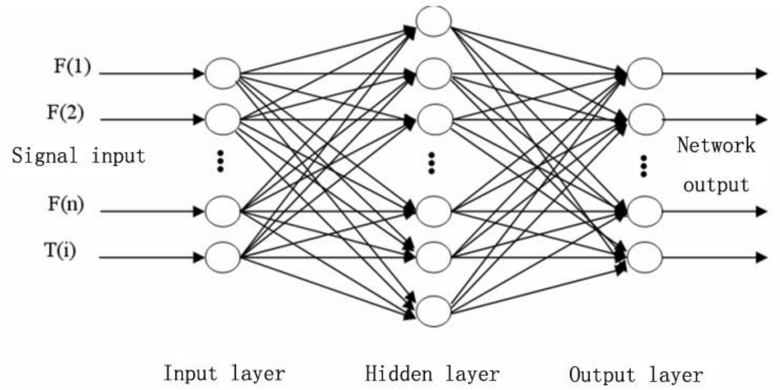

Fig. 8 Structure of BP neural network with three layers

The learning process of the algorithm is composed of forward and backward propagation [18]. In the forward propagation process, the input layer of the input mode through hidden layer processing is transmitted to the output layer, and each layer of neurons only affects the state of the next layer of neurons. If it can't get the desired output in the output layer, then it would make the back propagation. The error signal would be returned along the original connecting path, and it makes the error signal be minimized by modifying the weights of each neuron. Fig. 9 shows the flowchart of the back propagation network.

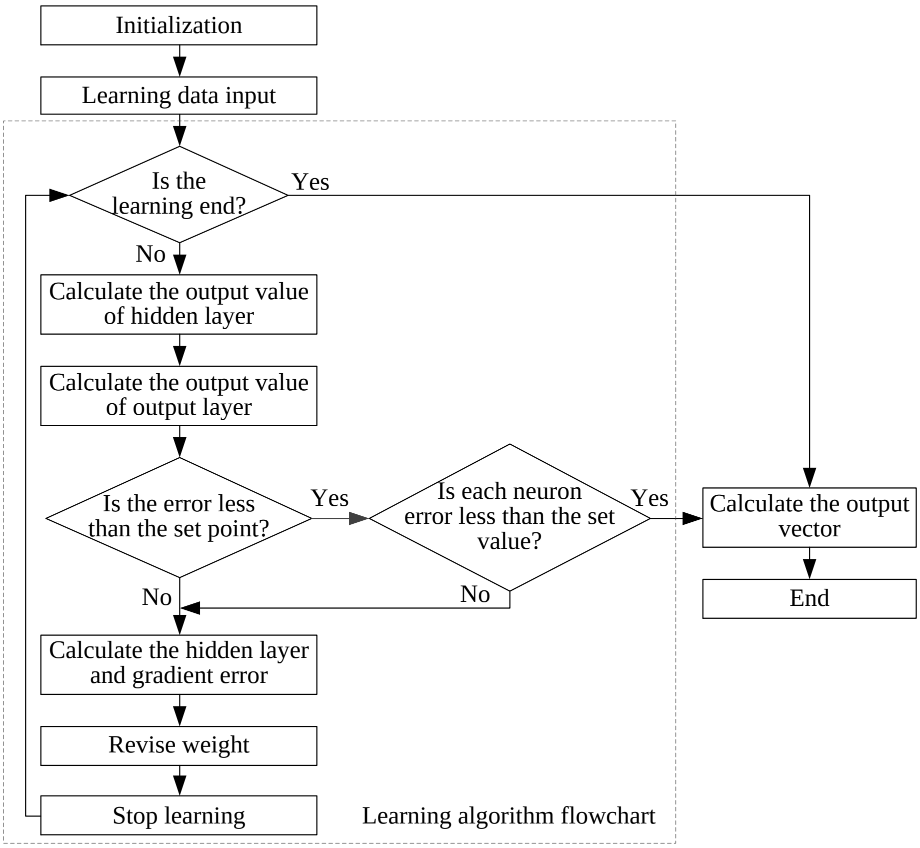

Fig. 9 Learning algorithm flowchart based on BP network

In the learning algorithm, it makes the output of a neuron multiply by one gain constant to transmit another neuron, namely the transfer function between the nodes is S-type function, and he expression is shown as in Eq. (2). The function curve is shown in Fig. 10, and the output of the feed forward neural network is in the range from 0 to 1.

$$f(x) = \frac{1}{1+\exp(-x)} \tag{3}$$

In Eq. (3), x is the sum of all inputs of a neuron plus a set of thresholds. If ω_{ij} represents the connecting weights of the neurons from i_{th} neuron to j_{th} neuron, θ_i represents the threshold of i_{th} neuron, O_1 represents its output, and then the output of i_{th} neuron is shown as in Eq. (3).

In order to describe the training phase of the neural network, all concepts in the structure shown in Fig. 9 are defined as follows: i – input parameter of the lowest layer, j – neuron parameter of hidden layer, k – neuron parameter of output layer, p – model parameter of training set, t_{pk} – target output of k_{th} output of the model P, o_{pk} – k_{th} output of neural network output of model P.

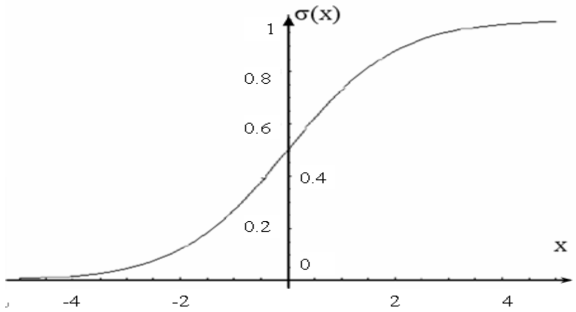

Fig. 10 Neuron transfer function

$$o_1 = \frac{1}{1+\exp[-(\sum_j \omega_{ij} o_j + \theta_i)]} \tag{4}$$

For each model, the error expression of the system is shown as in Eq. (5):

$$E_p = \frac{1}{2}\sum_k (t_{pk} - o_{pk})^2 \tag{5}$$

The average error expression of the system is shown as in Eq. (6):

$$E = \frac{1}{2}\sum_p \sum_k (t_{pk} - o_{pk})^2 \tag{6}$$

Assume each layer of the input layer, hidden layer and output layer of BP network owns N neurons. There is $2N^3 + N^2$ connecting points in the feed forward network, and there is $2N^2$ + N thresholds needed to be determined. In a 16×16 array of sensors, N is 256, namely there are 33751296 unknown values needed to be determined by iteration. It is obvious that if the larger the difference between the original value and the optimal value of starting calculating is, then the longer the consumed time is. To initialize neural network and make it work in a reasonable scope of work, the output value of the output neurons can be controlled in a range from 0.25 to 0.75. In this case, the maximum and minimum input of the neuron is −ln3 and ln3 by Eq. (2), respectively. Research shows that the training of neural network will not converge starting from the same connecting values, if a connecting point (such as ω_A) is between two identical parameters, then it will take the same parameter as the input unit excitation signal. Otherwise, the connection points will be seen as the crosstalk signal between different units to influence the excitation signal.

Assume the maximum input of each unit provided by sensing array as x_{max}. If all units such as the sensing array are excited, then the total input of neuron [i, j] in the input layer can be obtained by Eq. (7):

$$x_{\max}\omega_A + 8x_{\max}\omega_B + (N^2 - 9)x_{\max}\omega_C + \theta = +\ln 3 \tag{7}$$

If a sensing unit which has the same coefficient with the neuron [i, j] is excited, then the total input of the neuron can be obtained by Eq. (8):

$$x_{\max}\omega_A + 8(0)\omega_B + (N^2 - 9)(0)\omega_C + \theta = +\ln 3 \tag{8}$$

In the input layer, if a sensing unit that is far from the neuron is stimulated, then here is the Eq. (9):

$$(0)\omega_A + 8(0)\omega_B + (N^2 - 10)(0)\omega_C + \omega_C x_{\max} + \theta = -\ln 3 \tag{9}$$

If there is no sensing element to be excited, then there is Eq. (10):

$$(0)\omega_A + 8(0)\omega_B + (N^2 - 9)(0)\omega_C + \theta = -\ln 3 \tag{10}$$

By Eq. (9) and Eq. (5), it can be expressed as a matrix form:

$$\begin{bmatrix} x_{\max} & 8x_{\max} & (N^2-9)x_{\max} & 1 \\ x_{\max} & 0 & 0 & 1 \\ 0 & 0 & x_{\max} & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \omega_A \\ \omega_B \\ \omega_C \\ \theta \end{bmatrix} = \begin{bmatrix} \ln 3 \\ \ln 3 \\ -\ln 3 \\ -\ln 3 \end{bmatrix} \tag{11}$$

For the connecting point of the input layer and the middle layer, it can make the simulation analysis. In the connecting point between network input and input layer neurons, the feedback can be carried out by the output of the sensing array between 0 and x_{max}. The connecting points between the input layer and the middle layer can be feedback by the input layer neurons, and these neurons can provide the output from 0.25 to 0.75. Replacing 0.25 with 0 and x_{max} replacing 0.75, the connecting points between the input layer and the intermediate layer neuron can be obtained by Eq. (12):

$$\begin{bmatrix} 0.75 & 8(0.75) & (N^2-9)(0.75) & 1 \\ 0.75 & 8(0.25) & (N^2-9)(0.25) & 1 \\ 0.25 & 8(0.25) & (N^2-10)(0.25)+0.75 & 1 \\ 0.25 & 8(0.25) & (N^2-9)(0.25) & 1 \end{bmatrix} \begin{bmatrix} \omega_A \\ \omega_B \\ \omega_C \\ \theta \end{bmatrix} = \begin{bmatrix} \ln 3 \\ \ln 3 \\ -\ln 3 \\ -\ln 3 \end{bmatrix} \tag{12}$$

For connecting points between the intermediate layer and the output layer, the initial value calculation will be slightly different because of only one output neuron and the N^2 connecting points with the same form. First case, all sensing array units are excited, and the input of the output neurons can be represented by Eq. (13):

$$N^2(0.75)\omega + \theta = +\ln 3 \tag{13}$$

In second cases, all of the sensing array is not excited, and the result is represented by Eq. (14):

$$N^2(0.25)\omega + \theta = -\ln 3 \tag{14}$$

Eq. (12) and Eq. (13) can be expressed as Eq. (15) in a matrix form:

$$\begin{bmatrix} N^2(0.75) & 1 \\ N^2(0.25) & 1 \end{bmatrix} \begin{bmatrix} \omega \\ \theta \end{bmatrix} = \begin{bmatrix} \ln 3 \\ -\ln 3 \end{bmatrix} \tag{15}$$

The initial value θ and ω of neural network training can be obtained by Eq. (11), Eq. (12) and Eq. (13). In order to avoid the non-convergence in training, depending on the same connecting value or threshold, each actual initial value is obtained by calculating the value plus a small random number. Once these values have been determined, through the sample set provided by a composed of a set of known sensing array inputs and outputs, the neural networks can be learned through training to obtain the relationship between the total input and output of the sensing array unit.

The neural network training samples are provided by the three-dimensional calibration experimental data of the pressure, temperature and voltage of the tactile sensing array. Under different temperature conditions, the static input of the test pressure and output voltage, and the output characteristic parameters can be calibrated, it can be obtained the output voltage of the pressure, temperature and the sensing element and its normalized value. The interval between the input and output values of the transformation function is between 1 and 0, and the standard sample database of neural network input and output can be constituted by the normalized processing. It first makes the actual value of the output voltage signal and the external pressure of the 16×16 sensing array and the temperature signal of the environment constitute a sample set, then it can be used for training and testing of the neural network. Because the matrix is relatively large, it is inconvenient to be listed here one by one.

Experimental test of tactile sensing array

After completing the training, the neural network, it can make the processing for the output signal of the tactile sensing array. As long as the pressure is applied to the robot tactile sensing system, the neural network can give the corresponding output and display the state and distribution of the pressure. Because the neural network uses parallel computing, the running speed is very fast in practical application, and so, the pressure can be monitored in real time. In the laboratory, the authors have carried on the test to the robot tactile sensing suit system, and in pressure distribution, when there is an external force acting on the sensing suit, then the system can output the position and distribution of pressure, and output sensing array data in a tactile image display mode. Therefore it can easily achieve the high accuracy quantifying test of the pressure.

Under the environment temperature condition of 20 °C, the constant pressure of 10, 20 and 50 N are respectively applied on the tactile sensing suit, and each pressure is taken for 16 arbitrary action points. Through the calculating calibration data of the output voltage and sensing array, it can get the corresponding pressure. In these circumstances, the output voltage of the sensing unit respectively is 3.635 V and 2.410 V. It can be seen from Fig. 11, Fig. 12 and Fig. 13 shows that the output of the system is accordance with the voltage value of the actual calibration. The relative error is within 5%, and so the tactile sensor system can accurately measure the exerting pressure.

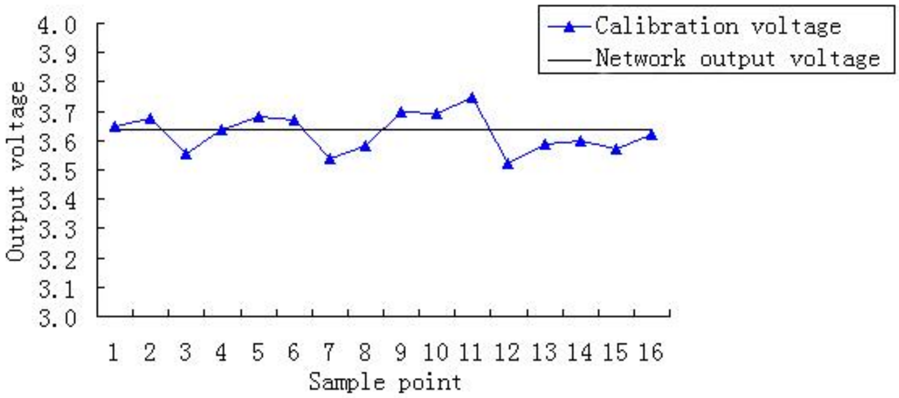

Fig. 11 Comparison value of output voltage and calibration at pressure being 10 N

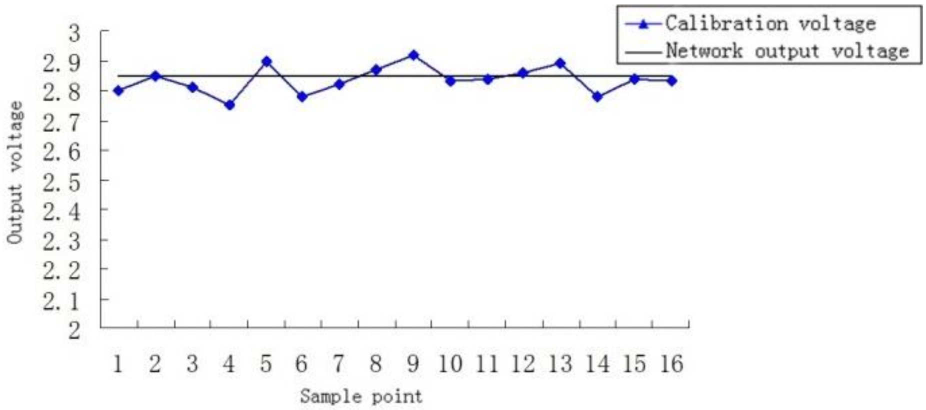

Fig. 12 Comparison value of output voltage and calibration at pressure being 20 N

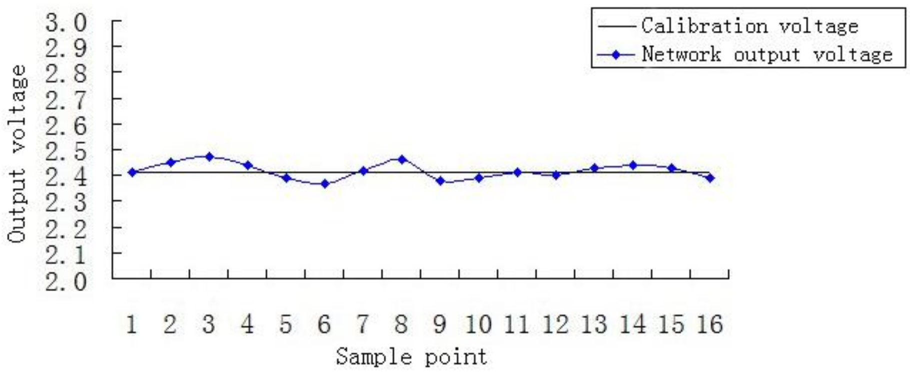

Fig. 13 Comparison value of output voltage and calibration at pressure being 50 N

Conclusions

Aimed at the crosstalk influence among the temperature, voltage fluctuations and between sensing signals of the sensing array unit existed in the robot tactile sensing suit, the paper presented a new information fusion strategy based on neural network. It takes BP based neural network as the fusion tool, makes fusion processing for tactile sensing signal, eliminates the effect of non-target parameters on sensing array, and improves the stability and accuracy of the system. By means of neural network processing model, it makes the processing for all acquired tactile data, and realizes the accurate identification in real time for the position of the contact pressure. Therefore, it can accurately determine the contact position of the robot's sensing suit, stress state and pressure distribution situation.

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