Research Article

Modeling Analysis and 3D Force Prediction of a Novel Piezoelectric Tactile Sensor

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To measure three-dimensional (3D) forces efficiently and improve the sensitivity of tactile sensors, a novel piezoelectric tactile sensor with a “sandwich” structure is proposed in this paper. An array of circular truncated cone-shaped sensitive units made of polyvinylidene fluoride (PVDF) is sandwiched between two flexible substrates of polydimethylsiloxane (PDMS). Based on the piezoelectric properties of the PVD F sensitive units, finite element modelling and analysis are carried out for the sensor. The relation between the force and the voltage of the sensitive unit is obtained, and a tactile perception model is established. The model can distinguish the sliding direction and identify the material of the slider loaded on the sensor. A backpropagation neural network (BPNN) algorithm is built to predict the 3D forces applied on the tactile sensor model, and the 3D forces are decoupled from the voltages of the sensitive units. The BPNN is further optimized by a genetic algorithm (GA) to improve the accuracy of the 3D force prediction, and fairly good prediction results are obtained. The experimental results show that the novel tactile sensor model can effectively predict the 3D forces, and the BPNN model optimized by the GA can predict the 3D forces with much higher precision, which also improves the intelligence of the sensor. All the prediction results indicate that the BPNN algorithm has very efficient performance in 3D force prediction for the piezoelectric tactile sensor.

1. Introduction

Obtaining useful tactile information from complex environment is particularly important to the development of robot technology. Tactile sensors have become one of the hot research topics in the robot field, and tactile sensors which could imitate the human skin play a key role in the intelligent robot area. According to the working principles, tactile sensors could be categorized into several groups such as piezoelectric sensors [1–5], capacitive sensors [6–10], piezoresistive sensors [11–13], and electromagnetic sensors [14–16]. A lot of researchers focused on the materials and the structures of the tactile sensors, and the research of multidimensional and multifunctional flexible tactile sensors based on neural network methods has gradually become the focus in electronic skin field. Wang and Song [17] presented a flexible tactile sensor with conductive rubber mate-

rial and proposed an efficient RBF neural network algorithm for multidimensional information prediction of the tactile sensor. Liu et al. [18] presented a novel flexible capacitive 3D tactile sensor using crossbar PDMS walls and micropillar arrays as a composite structure dielectric layer for the sensor, which shows great potential for applications in robot technology. In reference [19], the experimental results show that the piezoelectric properties of the soft PZT5 stacks are significantly improved under appropriate lower compressive stress and are deteriorated under higher compressive stress. In reference [20], the applicability of a piezoelectric layer in a conical shell vibration mitigation is vividly determined by using an optimal controller which decreases the actuator-applied voltage amplitude dramatically. Kim et al. [21] utilized the characteristics of piezoelectric materials to fabricate a multilayered cross-shaped piezoelectric sensor for torsional load analysis. Reference [22] developed a

procedure to optimize electromechanical coupling across multiple vibration modes for a representative turbomachinery blade with surface-mounted piezoelectric patches. Reference [23] constructed a framework allowing the easy usage of the integrated sensor array platforms as highly sensitive electronic skins for mapping spatial pressure distribution and monitoring of the human physiological signals. Xu et al. [24] proposed a novel three-dimensional force flexible tactile sensor made through “overall injection molding” technique. Acer et al. [25] proposed a silicone-embedded, low-profile piezoelectric sensor array that is suitable for applications where tactile sensing and force localization are needed. Chen et al. [26] proposed a pressure sensor with nanowires/graphene heterostructures for static measurements based on the synergistic mechanisms between strain-induced polarization charges in piezoelectric nanowires, which shows great potential in the application of the electronic skin. Lee et al. [27] prepared a multimodal electronic skin, and it can identify and distinguish not only mechanical stresses from a single stimulus such as pressure and tensile strain but also those from a combination of multiple stimuli.

There are also many works that use neural network (NN) methods to estimate or measure forces applied on the sensor. Jie-Han et al. [28] conducted an experiment of a neural network to collect sufficient samples for training, validation, and testing, and the results demonstrated that the neural network could estimate impact force and active force with average errors ranging between 0.10 and 0.18 of BW at different running speeds. Urda et al. [29] proposed an efficient method for the experimental measurement of the lateral wheel-rail contact force based on artificial neural networks (ANNs), and they demonstrated how an artificial intelligent method proves to be a valid alternative to other approaches based on sophisticated mathematical models when it is applied to the wheel-rail contact force measurement. In reference [30], different ANN approaches had been proposed to predict the response of a fiber optic microbend sensor and performance comparison demonstrated that all the ANN models used in the paper can predict the sensor responses with considerable errors, which means that ANNs can be used as useful tools in the design of the sensors with high robustness.

To improve the performance of a tactile sensor and to detect 3D forces accurately, this paper focuses on the structure design, material selection, and 3D force prediction of the tactile sensor. Based on the piezoelectric effect and force-sensitive characteristics of PVDF, a flexible tactile sensor with a “sandwich” structure is designed. The sensor mainly consists of three layers, namely, an upper PDMS flexible film layer, a piezoelectric layer composed of 2×2 sensitive unit array, and a lower PDMS substrate layer. The finite element analysis for the sensor is carried out. The relation between the force and the voltages of the sensitive units is obtained, and the sensor can recognize the moving direction and the material of the slider on it. After that, a BPNN model is built to predict the 3D forces applied on the tactile sensor model efficiently, which makes the sensor intelligent and smart. This paper is organized as follows. Section 2

presents the model of the piezoelectric tactile sensor. Section 3 elaborates the experiments of finite element analysis for the sensor. Section 4 reports and analyzes the process of the 3D force prediction based on the BPNN algorithm for the piezoelectric tactile sensor model from different aspects. Section 5 presents the conclusions of this paper.

2. Model of the Piezoelectric Tactile Sensor

2.1. Construction of the Sensor Model. Polyvinylidene fluoride (PVDF) is an organic piezoelectric material. It is known as the piezoelectric polymer and has the advantages of good flexibility, wide frequency response range, high corrosion resistance, etc. [31, 32].

In this paper, the PVDF is chosen to be the material of the sensitive units (shown in Figure 1) of the piezoelectric tactile sensor. We had tried several structures for sensitive units, but after many times of experiments and careful analysis, it is found that the simulation results of those structures are not as good as the structure of circular truncated cone. So, the shape of the sensitive unit is designed as a solid circular truncated cone used to transform mechanical energy into electrical energy. It can increase both the stability and the sensitivity of the sensor. The diameters of the top surface and the bottom surface of the sensitive unit are 0.25 mm and 2 mm, respectively. The height of the sensitive unit is 0.5 mm. In Figure 1, “1” and “2” denote the electrodes of the sensitive unit.

Based on the piezoelectric effect and the force-sensitive characteristics of PVDF, a flexible tactile sensor with a “sandwich” structure is designed, as shown in Figure 2. The sensor mainly consists of an upper PDMS flexible film, a piezoelectric layer, and a lower PDMS flexible substrate. In Figure 2, “1” and “3” represent the upper PDMS flexible film and the lower PDMS flexible substrate, respectively. The thickness of the PDMS film is 0.25 mm, and the length and width of the PDMS film for the sensor are both 6 mm. The flexible film is used to prevent the sensitive units from being damaged by the direct action of an external force and is also used to transfer the force to the piezoelectric layer. The lower substrate of the PDMS is used to support the sensitive units and to make them stable. In Figure 2, “2” represents the piezoelectric layer, which is mainly composed of a 2×2 sensitive unit (shown in Figure 1) array. The array can detect the direction of tactile sensation applied on the sensor precisely and make the experiment easier. The distance between the center of two adjacent sensitive units is 3 mm, and the gap around the sensitive units is filled with PDMS to improve the flexibility of the sensor (this part is hidden in Figure 2 for the convenience of observing the internal structure of the sensor). The size of the model shown in Figure 2 is 6 mm $\times$ 6 mm $\times$ 1 mm, which is easy to manufacture.

2.2. Principle Analysis. When a piezoelectric material is deformed by an external force in a certain direction, internal polarization will take place with the positive and negative charges appearing on its two opposite surfaces, as shown in Figure 3. That phenomenon of converting mechanical energy into electrical energy is called the positive

FIGURE 1: The model of sensitive unit. (a) The overall schematic diagram. (b) The top view. (c) The side view.

FIGURE 2: The structure of the sensor.

FIGURE 3: Positive piezoelectric effect.

piezoelectric effect. When the external force is removed, the material will return to the status of no charge. On the contrary, when an electric field is applied in the direction of polarization, the piezoelectric material will be deformed. When the electric field is removed, the deformation will disappear and that phenomenon of converting electrical energy into mechanical energy is called inverse piezoelectric effect. In this paper, the PVDF with piezoelectric effect is taken to make the sensitive units of the piezoelectric layer for the tactile sensor.

There are two common forms of constitutive equations for the piezoelectric effect, which are the strain-charge form

and stress-charge form. The strain-charge piezoelectric constitutive equations [33] are shown as follows:

$$\begin{aligned} S &= AX + B^T E, \\ D &= BX + \epsilon_0 \epsilon_{rX} E, \end{aligned} \quad (1)$$

where S is the strain, X is the stress, E is the electric field, and D is the electric displacement field; A , B , ϵ_{rX} , and ϵ_0 represent the flexibility matrix, the piezoelectric coefficient matrix, the relative permittivity under constant pressure, and the vacuum dielectric constant, respectively.

The stress-charge piezoelectric constitutive equations are shown as follows:

$$\begin{aligned} X &= C_E S + G^T E, \\ D &= GS + \epsilon_0 \epsilon_{rS} E, \end{aligned} \quad (2)$$

where C_E , G , ϵ_{rS} , and ϵ_0 represent the rigidity matrix, coupling matrix, relative dielectric constant, and the vacuum dielectric constant, respectively.

TABLE 1: Material properties.

Material	Density (kg/m ³)	Relative permittivity	Young's modulus (kPa)	Poisson ratio	e_{33} (C/m ²)
PVDF	1780	{7.4,9.3,7.6}	2.45×10^6	0.4	-0.027
PDMS	970	2.75	750	0.49	/

In this paper, the strain-charge form of the piezoelectric equation involved is used.

The PDMS material of the piezoelectric sensor studied in this paper has the mechanical properties as rubber materials, and its constitutive relationship [34] is as follows:

$$S = \frac{\partial W}{\partial E} = 2 \frac{\partial W}{\partial C}. \quad (3)$$

In equation (3), S is the second stress tensor, W is the strain energy density function, C is the Cauchy-Green strain tensor, and E is the Lagrange strain tensor.

3. Finite Element Simulation

3.1. Finite Element Modeling. The COMSOL Multiphysics tool is used to carry out finite element analysis for the piezoelectric tactile sensor model shown in Figure 2 and to solve the coupling problems in the solid mechanics module and the electric module. Then, the sensor model could be analyzed and calculated accurately. To ensure the accuracy of the external force transferred from the PDMS films to the PVDF sensitive units, in the simulation modeling, the PDMS films and the PVDF sensitive units of the sensor are set up as an assembly structure. In this way, when an external load or force acts on the upper PDMS film of the sensor, it could be transferred to the PVDF sensitive units. In the finite element analysis, each surface in contact between PDMS films and PVDF sensitive units is set as a contact pair to prevent the model from penetrating. The penalty function is used to set the contact condition for the contact pairs, and the imprints from the contact pairs would be reserved for the selection of different finite element domains in the simulation.

As the coupling simulation of the force field and electric field needs to be performed, the main properties such as density, relative permittivity, Young's modulus, and Poisson ratio are set for both PVDF sensitive units and PDMS films to meet the requirements of the flexible tactile sensor, shown in Table 1.

The mechanical boundary condition and the electric field boundary condition are arranged for the sensor. The lower PDMS flexible substrate of the sensor is fixed by the constraint command; then, it could simulate the state of the sensor when it is placed horizontally. Voltages are generated during the deformation process from the piezoelectric layer, which are the potential differences between the equipotential surfaces along the polarization direction of the piezoelectric layer. The lower surface of the piezoelectric layer is grounded (i.e., zero potential). Thus, the voltage detected from the upper surface is the voltage generated by the piezoelectric layer.

3.2. Simulation Experiments. When a force is applied on the upper flexible film of the sensor, the sensitive units of the piezoelectric layer will deform accordingly. The simulation result of the sensitive unit in Figure 2 subjected to a normal force of 1N is shown in Figure 4. Due to the piezoelectric effect of PVDF, when the sensitive unit is deformed by an external force, positive and negative charges appear on its two opposite surfaces. After the external force is removed, it returns to the initial state.

In the simulation, the normal force applied on the upper PDMS film of the sensor is evenly distributed on each sensitive unit. When the normal force F_z of 1N is applied to the upper surface of the sensor, the simulation results are shown in Figure 5. The color legend indicates the voltage value precisely, and it can be seen that the voltage of the upper surface of the sensitive unit is higher than the other part. The main reason is that the upper surface of the sensitive unit is close to the position where the pressure is loaded.

As the sensor model with 2×2 sensitive units is symmetrical, the same simulation effect would be produced when the same magnitude of tangential force F_x and F_y is applied to the sensor. Therefore, the following experiments will mainly focus on the situation that the tangential force F_x applied to the sensor. A tangential force F_x of 1N is applied to the PDMS film on the upper layer of the sensor, and the voltage distribution diagram is shown in Figure 6. The result shown in Figure 6 is different from the case of applying the normal force. When the tangential force F_x is applied, the potential on the upper surface of the sensitive unit in Figure 6 is relatively lower than that generated by normal force F_z . That phenomenon is caused by the polarization direction of the PVDF. In the simulation experiment, z -axis polarization is adopted for the PVDF. As the normal force applied along the same direction of the polarization direction increased, the voltage value generated from the sensitive unit would be increased. As the angle between tangential force and the polarization direction is 90° , the corresponding voltage value generated by the tangential force is deeply decreased.

In the simulation, different values of the tangential force F_x and the normal force F_z are applied to the sensor. The relation between the normal force and the voltage and the relation between the tangential force and the voltage are both gained (shown in Figure 7).

In Figure 7, ten samples are used to fit the relationship between the normal force and the voltage and the relationship between the tangential force and the voltage. The normal force and the tangential force are both in the range of [0N, 1N]. As the normal force or the tangential force increased, the corresponding voltage increased correspondingly. The relation between the force component and the voltage is approximately linear. In Figure 7, the sensitivities

FIGURE 4: Deformation of the sensitive unit. (a) The initial state of the sensitive unit when there is no force applied. (b) The deformation state when the sensitive unit is subject to a normal force of 1N.

FIGURE 5: Simulation result of the sensor when it is subject to the normal force of 1N.

FIGURE 6: Simulation result of the sensor when it is subject to a tangential force of 1N.

of the sensor are 5.4 V/N (the slope of the black line) under the action of normal force and 0.61 V/N (the slope of the red line) under the action of tangential force, respectively. The results show that the sensitivity of the sensor under the normal force is much greater than that under the tangential force. It means that the normal force could be well sensed

by the sensitive units and there exists weak correlation between normal force F_z and other force components. That would make the decoupling process easier.

As the relationship between the force and the voltage is gained, the basic tactile sensing function of the sensor could be realized through further simulation experiments. Based

FIGURE 7: The relation between the voltage and the force.

on the previous piezoelectric experiment, a small slider made of copper with the size of $4 \text{ mm} \times 0.6 \text{ mm} \times 0.1 \text{ mm}$ is put on the upper surface of the sensor and it is allowed to slide freely on the surface. The length of 4 mm enables the small slider to cover the spots near the center of the corresponding sensitive units during the sliding process, so as to accelerate the speed of simulation calculation; the width of 0.6 mm is exactly one-tenth of the length of the PDMS films, which ensure that the sliding of the small slider could be completed in an integer second (the ninth second) in both the horizontal sliding experiment and the vertical sliding experiment; the height of 0.1 mm makes it difficult for the small slider to roll over.

In the experiment, the lower surface of the slider and the upper surface of the sensor are in contact with each other and the slider would be affected by friction during the sliding process. By changing the moving direction of the slider, different experiments have been carried out while keeping other conditions unchanged. Figure 8 shows the sliding experiments in the simulation, where the copper slider on the surface of the sensor moves along the positive direction of the y -axis and x -axis accompanied by the speed of $0.6 \times 10^{-3} \text{ m/s}$, respectively. V1, V2, V3, and V4 shown in Figure 8 represent the average voltages on the upper surface of the four sensitive units, and their values changed according to the moving state of the slider.

During the simulation, the slider slides to different positions changing the voltages of the corresponding sensitive units. According to the corresponding relationship between the force and the voltage, when the slider slides near the center of each sensitive unit, the force that the slider loads on the sensitive unit would reach an extreme value. At that moment, the average voltage of the corresponding sensitive unit would reach a peak value. As shown in Figure 8(a), when the slider slides at $0.6 \times 10^{-3} \text{ m/s}$ for 0.4 seconds and 7.4 seconds, it arrives the center of the corresponding sensitive units; meanwhile, the peaks of V1 and V2 also appear at the 0.4 second and 7.4 second, respectively, as shown in

Figure 9. In Figure 9, the peaks of V1 and V2 are the voltages generated when the slider slides to the center of the corresponding sensitive units shown in Figure 8(a), which is consistent with the actual situation. Adjusting the slider to the vertical position as shown in Figure 8(a), which means that let the slider slide along the positive direction of x -axis with the same speed ($0.6 \times 10^{-3} \text{ m/s}$), and the description is shown in Figure 8(b). The voltage curves of the corresponding sensitive units are shown in Figure 10, where the peaks of V1 and V4 represent the voltage generated when the slider slides to the center of the corresponding sensitive units. When the slider moves at the speed of 0.6 mm/s , it arrives at the opposite side at the 9th second and the whole sliding process ends. As shown in Figures 9 and 10, each interval of the horizontal axis represents the moving time is which 1 second and the corresponding moving distance is 0.6 mm .

It can be seen from the sliding experiment that when the slider moves on the surface of the sensor, the sliding direction could be judged by the voltage value of the sensitive unit when the slider arrives at the specific position. For example, during the sliding process shown in Figure 9, the voltage value of V1 changed from the beginning and it reached the peak at 0.4 seconds. At this point, the slider reached above the center of the sensitive unit indicated by V1 in Figure 8(a). Accordingly, the voltage value of V2 started to change at around 4 seconds and it reached the peak at 7.4 seconds. At that point, the slider reached above the center of the sensitive unit indicated by V2 in Figure 8(a). According to the time when the values of V1 and V2 changed and the time when their peak values appeared, it could be inferred that the sliding direction of the slider is the positive direction of the y -axis. Therefore, the sensor can recognize the direction of the contact force. The positive direction of the x -axis, the negative direction of the y -axis and the negative direction of the x -axis for the sliding direction can be inferred in the same way.

Then, the slider in the same size ($4 \text{ mm} \times 0.6 \text{ mm} \times 0.1 \text{ mm}$) but made of different materials (such as copper, iron, silicon, and PDMS) put on the surface of the sensor sliding along y -axis with the same speed of $0.6 \times 10^{-3} \text{ m/s}$ is used to detect whether the sensor could distinguish the slider made of what material by the changing voltages. The results are shown in Figure 11. Figure 11 shows the variation of the average voltage V1 during the sliding process when the slider made of different materials is moving. The results show that although the sliders made of different materials have the same size, the voltages generated during their sliding process are significantly different. The material of each slider could be recognized from the peak value of the voltage. In the experiment, the period from the starting point of the slider to the time the slider arrives the first sensitive unit is taken as the interval to simplify the calculation of the finite element analysis. In about 0.65 s (which means that the interval is 0.65 s), the slider reaches the center point of the PVDF sensitive unit. At that time, the slider made of what material could be observed intuitively and clearly by the different voltage values. In Figure 11, the maximum value of the voltage peak corresponds to the slider made by silicon; correspondingly, the minimum value of the voltage peak corresponds to the

(a) The slider moves along the positive direction of the y-axis

(b) The slider moves along the positive direction of the x-axis

FIGURE 8: The simulation of sliding for the sensor.

slider made by copper. The main reason of that phenomenon is that a different material has a different density. The higher the density of the slider is, the greater the force would be transmitted to the sensitive unit under the slider, which would produce greater voltage of the sensitive unit.

The results of Figure 11 concludes that the different voltages measured from the sensor could reveal the main material of the slider loaded on the sensor, which can broaden the application field of the sensor. The experiments in Figures 8 and 11 are conducted on the basis of the experiment results in Figure 7. Their essences are based on the piezoelectric effect, and they are the function extension of the piezoelectric tactile sensor. The mapping relation between the force and the voltage gained in Figure 7 is under the ideal condition. In practical application, since there exists coupling relation between signals, the relation between force and voltage of the tactile sensor is often nonlinear. In this paper, the

BP neural network (BPNN) algorithm with strong approximation ability is used to decouple the mapping relation between the external force and the output voltage of the sensitive unit from different aspects and to predict the 3D force applied to the sensitive units precisely.

4. 3D Force Prediction Based on the BPNN Algorithm for the Sensor

4.1. Basic Principle of the BPNN Algorithm. A BPNN is a multilayer feedforward network with error backpropagation [35]. The BPNNs used in this work are all composed of three layers: an input layer, a hidden layer, and an output layer. The basic structure of a three-layer BPNN is shown in Figure 12.

In Figure 12, V represents the connection weight matrix between the neurons in the input layer and the neurons in

FIGURE 9: The status of V1 and V2 during the sliding process along the positive direction of the y -axis.

FIGURE 10: The status of V1 and V4 during the sliding process along the positive direction of the x -axis.

FIGURE 11: The corresponding voltages of the sensitive unit by different materials during the sliding process.

FIGURE 12: Structure of the three-layer BPNN.

the hidden layer and W represents the connection weight matrix between the neurons in the hidden layer and the neurons in the output layer. The implementation of the BPNN algorithm consists of two parts: signal forward propagation and error backpropagation. In the signal propagation process, the input signal is propagated from the input layer to the hidden layer and then transmitted to the output layer. The equations for the input α_h and the output μ_h of the h th neuron in the hidden layer are as follows:

$$\begin{aligned}\alpha_h &= \sum_{i=1}^d v_{ih} x_i - b, \\ \mu_h &= f(\alpha_h),\end{aligned}\quad (4)$$

where v_{ih} represents the connection weight between the i th neuron in the input layer and the h th neuron in the hidden layer, x_i is the input signal of the i th neuron in the input layer, b is the threshold of the hidden layer, d is the number of the neurons in the input layer, and f is the transfer function of the hidden layer. The transfer function constructed in this paper is expressed as follows:

$$f(x) = \frac{1 - e^{-\alpha x}}{1 + e^{\alpha x}}. \quad (5)$$

The relationship between the input β_j and the output y_j of the j th neuron in the output layer is expressed as follows:

$$\begin{aligned}\beta_j &= \sum_{h=1}^n w_{hj} \mu_h, \\ y_j &= g(\beta_j),\end{aligned}\quad (6)$$

where w_{hj} represents the connection weight between the h th neuron in the hidden layer and the j th neuron in the output layer, n is the number of the neurons in the hidden layer, and g represents the transfer function of the output layer. The function constructed in this paper is expressed in equation (7) as follows:

$$g(x) = kx + c. \quad (7)$$

The input signal is propagated from the input layer to the hidden layer and finally to the output layer. If the output of the output layer does not match the expected output, the error backpropagation process would be started.

In the error backpropagation process, the output error is transmitted from the output layer to the hidden layer and then

arrives at the input layer. Meanwhile, the error is distributed to all neurons in each layer and the error signal obtained from each layer is used as the basis for the adjustment of the connection weight of the network. After repeated learning and training, when the mean square error of the network is less than the set value or the number of iterations reaches the preset value, the training process will be stopped. In this paper, the maximum number of iterations is 1000 and the mean square error is 0.001. The mean square error E , the correcting weight v'_{ih} between the i th neuron of the input layer and the h th neuron of the hidden layer, and the correcting weight w'_{hj} between the h th neuron of the hidden layer and the j th neuron of the output layer are defined as follows:

$$\begin{aligned}E &= \frac{1}{q} \sum_{m=1}^q (F'_m - F_m)^2, \\ v'_{ih} &= v_{ih} + \eta E_h \frac{\partial f(e)}{\partial(e)} x_i, \\ w'_{hj} &= w_{hj} + \eta E_j \frac{\partial g(e)}{\partial(e)} x_h,\end{aligned}\quad (8)$$

where η denotes the learning rate, F_m denotes the expected output of the m th sample, F'_m denotes the predicted output of the m th sample, q denotes the number of the samples, E_h denotes the error of the h th neuron in the hidden layer, e denotes the cumulative sum of every input value multiplied by the corresponding connection weight, and E_j denotes the error of the j th neuron in the output layer.

In this paper, F_m includes three components: F_{m_x} , F_{m_y} , and F_{m_z} . F_{m_i} ($i = x, y, z$) is the expected output of 3D force components for the m th sample. F'_m includes three components: F'_{m_x} , F'_{m_y} , and F'_{m_z} . F'_{m_i} ($i = x, y, z$) is the predicted output of 3D force components for the m th sample.

4.2. Prediction of 3D Force Based on the Basic BPNN Algorithm

4.2.1. The BPNN Model for the Sensor. In the experiment, the upper PDMS film of the sensor shown in Figure 2 is divided into 4 rectangular areas of the same size (3 mm × 3 mm), as shown in Figure 13. Under each rectangular area, there is a sensitive unit. The voltages from the 4 sensitive units could be detected when a 3D force is exerted on. 500 different 3D forces in the range of [0N, 3N] are applied on one of the 4 rectangular areas (3 mm × 3 mm) for 500 times. Each time, a 3D force is applied to the rectangular area and the rectangular area is selected randomly. The 3D force applied to the sensor is according to the “body load” form in the finite element analysis, which is different from the form of loading force at the center of the rectangular area. The “body load” ensures that the force could be evenly distributed in the area. Accordingly, 2000 voltages from the 4 sensitive units could be detected, which are used as the training sample set of the BPNN. That is, each training sample contains an external 3D force applied to

FIGURE 13: The schematic of the sensor with the upper PDMS layer being divided into four areas.

the rectangular area and the output voltages of the 4 sensitive units. Then, one of the 4 areas is randomly selected for 50 times. Each time, a 3D force that belongs to $[0\text{N}, 3\text{N}]$ is applied to an area which is chosen randomly. Meanwhile, 200 voltages from the 4 sensitive units are obtained, which are taken as the testing sample set of the BPNN.

In this paper, the BPNN predictor is constructed to approximate the mapping relationship between the voltage values of the sensitive units and the 3D force applied on the sensor. The voltage $U = [V1, V2, V3, V4]^T$ of the 4 sensitive units generated by a 3D force is taken as the input signal vector of the BPNN input layer. Accordingly, the 3D force $F = [Fx, Fy, Fz]^T$ applied to the sensor is taken as the expected/target output vector of the BPNN output layer. That is, there are 4 neurons in the input layer and 3 neurons in the output layer of the BPNN. In this paper, the transfer function of the hidden layer for the BPNN is the hyperbolic tangent S-type function, as shown in equation (5) and the transfer function of the output layer is the linear transmission function, as shown in equation (7). After repeated experiments, the best results are obtained as the number of neurons in the hidden layer is 3. In the following experiment, the number of neurons is 4 in the input layer, 3 in the hidden layer, and 3 in the output layer for the constructed BPNN. By taking full advantage of the approximation ability of BPNN, the training samples are used to train the BPNN and to decouple the relationship between the 3D force and the voltages of the sensitive units. After the training process, the BPNN model is gained. In this work, the three-layer BPNN constructed in this way could predict the 3D forces accurately.

4.2.2. Analysis and Discussion of 3D Force Prediction Results. The relative error is used to evaluate the accuracy of the prediction result. The smaller the relative error is, the higher the

FIGURE 14: Prediction results based on BPNN.

TABLE 2: Relative prediction errors of 3D force component F_i .

	Minimum relative error of F_i	Average relative error of F_i	Maximum relative error of F_i	MSE
F_x	2.1%	17.3%	46.6%	0.0135
F_y	1.1%	6.7%	15.1%	0.0131
F_z	0.6%	4.2%	8.3%	0.0144

prediction accuracy would be. It is expressed as equation (9) as follows:

$$\delta_i = \frac{|F'_i - F_i|}{F_i}, \quad i = x, y, z. \quad (9)$$

In this paper, F_x , F_y , and F_z are the original 3D force, F'_x , F'_y , and F'_z are the predicted results by the BPNN, and δ_i is the relative prediction error of F_i ($i = x, y, z$). The average relative prediction error $\bar{\delta}_i$ of the n testing samples is defined as equation (10) as follows:

$$\bar{\delta}_i = \frac{1}{n} (\delta_{i_1} + \dots + \delta_{i_k} + \dots + \delta_{i_n}), \quad i = x, y, z, \quad (10)$$

where δ_{i_k} is the relative error of the k th sample and n is the number of testing samples.

Based on the above assessment method, the prediction results of the 3D forces obtained by the BPNN model are shown in Figure 14 and Table 2. Figure 14 shows the prediction results of 3D forces of the 50 testing samples. Table 2 shows the relative prediction errors of the 3D forces corresponding to Figure 14.

In Figure 14, the red triangles and the blue triangles represent the original values of F_x and the predicted results of

FIGURE 15: Prediction results of the 3D force.

F_x , respectively, that is F'_x . The red stars and the blue stars, respectively, represent the original values of F_y and the predicted result of F_y , respectively, that is F'_y . The red circles and the blue circles represent the original value of F_z and the predicted result of F_z , respectively, that is F'_z . The results show that most of the predicted values based on the BPNN model are very close to the original values of F_x , F_y , and F_z .

The results in Table 2 are corresponding to those in Figure 14. According to Figure 14 and Table 2, the average relative errors of F_x , F_y , and F_z for the testing samples are 17.3%, 6.7%, and 4.2%, respectively. The minimum relative errors of F_x , F_y , and F_z are 2.1%, 1.1%, and 0.6%, respectively, and the corresponding maximum relative errors are 46.6%, 15.1%, and 8.3%, respectively. The prediction results imply that the average relative error of normal force F_z is obviously less than those of tangential force F_x and F_y , which means that the prediction accuracy of F_z is much better than those of F_x and F_y . The main reason is that there may be large dimensional coupling between F_x and F_y of the input signal, which leads to the mutual interference between signals and causes the larger prediction error. Due to the difference between the sensitivities of polarized PVDF along the x -axis direction and y -axis direction, when a tangential force F_x and a tangential force F_y are loaded on the

TABLE 3: Comparison of 3D force prediction errors.

	Average relative errors without the GA	Average relative errors with GA optimization
$\bar{\delta}_x$	17.3%	13.8%
$\bar{\delta}_y$	6.7%	5.9%
$\bar{\delta}_z$	4.2%	3.8%

TABLE 4: Comparison of 3D force prediction results with different methods.

Prediction methods	Average relative errors		
	$\bar{\delta}_x$	$\bar{\delta}_y$	$\bar{\delta}_z$
BPNN without the GA	17.3%	6.7%	4.2%
BPNN optimized by the GA	13.8%	5.9%	3.8%
LM [38, 39]	5.1%	8.99%	12.3%
Standard BPNN [40]	17.2%	17.2%	18.5%

sensor at different time, the voltage values generated by the PVDF sensitive units are different because of the piezoelectric effect, which leads to the difference in the prediction results of F_x and F_y . In the experiment, the correlations between F_y and other components are weaker than the correlations between F_x and other components. So, the prediction errors of F_y are much lower than those of F_x . The results show that the BPNN algorithm can be well applied for the 3D force prediction of the piezoelectric tactile sensor.

4.3. Prediction of the 3D Force Based on BPNN Optimized by the Genetic Algorithm (GA)

4.3.1. BPNN Optimized by the GA. The GA is a classical method for searching for optimal solutions by simulating natural evolutionary processes [36, 37]. In this paper, the GA is utilized to optimize the basic BPNN model by optimizing the weights between the neurons in adjacent layers and to realize the high precision prediction of the 3D force applied on the sensor. First of all, the problem to be solved should be coded. Binary coding is adopted, where “1” means that the corresponding weight or threshold will be selected and “0” means that the weight or threshold will be dropped. Then, the initial population size is set as 50 which is the number of testing samples. In the experiment, the reciprocal of the sum of squared errors is used as the fitness function of GA to evaluate the adaptability of each individual sample. Accordingly, the selection, crossover, and mutation operations are carried out. The fitness function is shown in equation (11).

$$f = \frac{1}{\sum_{i=x}^z \sum_{m=1}^n (F'_{m_i} - F_{m_i})^2}, \quad i = x, y, z. \quad (11)$$

In equation (11), F_{m_i} ($i = x, y, z$) denotes the expected outputs of 3D force components for the m th sample, while

FIGURE 16: Fitness function values.

FIGURE 17: Sum of the squared errors.

$F'_{m_i} (i = x, y, z)$ denotes the predicted outputs by the BPNN model optimized by GA.

4.3.2. Results and Discussion. The results of the 3D force prediction without and with GA optimization for the 50 testing samples are shown in Figure 15 and Table 3.

In Figure 15, blue triangles, turquoise triangles, and red triangles represent the original values of F_x , the prediction results of F_x by BPNN without a GA, and the prediction results of F_x by BPNN optimized by a GA, respectively; blue stars, turquoise stars, and red stars represent the original values of F_y , the prediction results of F_y by BPNN without a GA, and the prediction results of F_y by BPNN optimized

by a GA, respectively; blue circles, turquoise circles, and red circles represent the original values of F_z , the prediction results of F_z by BPNN without a GA, and the prediction results of F_z by BPNN optimized by a GA, respectively.

The data given in Table 3 and Figure 15 clearly show that the prediction results of the 3D force based on the BPNN optimized by the GA are significantly improved comparing with the results without a GA optimization. The average relative prediction errors of the optimized BPNN for F_x , F_y , and F_z are 13.8% ($\bar{\delta}_x$), 5.9% ($\bar{\delta}_y$), and 3.8% ($\bar{\delta}_z$), respectively, which are 3.5 percentage points, 0.8 percentage points, and 0.4 percentage points lower than those prediction errors of BPNN without a

GA optimization, respectively. The experimental results show that a GA method can improve the approximation ability of BPNN effectively, improve the prediction accuracy of 3D force loaded on the sensor, and be well applied to the research of 3D force prediction for the piezoelectric tactile sensor.

The results in Table 3 are compared with the results reported in references [38–40]. The comparison of the related results is shown in Table 4.

It can be seen in Table 4 that the relative prediction errors of the BPNN optimized by the GA for F_x , F_y , and F_z are 13.8% ($\bar{\delta}_x$), 5.9% ($\bar{\delta}_y$), and 3.8% ($\bar{\delta}_z$), respectively, which are 3.4 percentage points, 11.3 percentage points, and 14.7 percentage points lower than the prediction errors of the standard BPNN in reference [40], respectively. Similarly, the result of $\bar{\delta}_y$ (5.9%) and $\bar{\delta}_z$ (3.8%) based on the BPNN optimized by the GA are 3.1 percentage points and 8.5 percentage points lower than those corresponding results based on the LM, respectively. The results imply that BPNNs have great performance in 3D force prediction. Especially, the BPNN optimized by the GA improves the results of 3D force prediction and makes the sensor smarter.

The variation of fitness function values of the BPNN optimized by the GA is shown in Figure 16. As can be seen in Figure 16, the value of fitness function increases sharply with the number of iterations when it is less than 20 and the increase slows down when the number of iterations is between 20 and 80. Until the number of iterations reaches 80, the mean square error of the BPNN's output is less than the set value of 0.001. After that, even if we keep training the optimized BPNN, the value of the fitness function does not improve further.

The variation of the sum of squared errors of the 3D force prediction during the training process of the BPNN optimized by the GA is shown in Figure 17. In Figure 17, at the initial stage, with the increase of training time, the sum of the squared error of the 3D force predicted by the optimized BPNN decreases sharply. After the neural network is trained 7 times, the decrease of the sum of squared errors slows down. After 80 times of training, there is almost no change in both the fitness function values and the sum of squared errors. The experimental results show that it is not true that the more the training time is, the better the prediction result will be. Too many times' training may lead to overfitting and decrease the performance of the network.

5. Conclusions

A flexible tactile sensor based on the piezoelectric polymer PVDF is proposed. According to the piezoelectric effect of PVDF, the finite element modeling and analysis are conducted for the sensor. The relation between the force and the voltage of the sensitive unit is gained, and the sensor can efficiently detect the 3D force loaded on the sensor. A tactile perception model is established, and the sensing model based on the tactile sensor can distinguish the sliding direction and identify the material of the slider put on the sensor. A basic BPNN model is constructed and used to pre-

dict the 3D force loaded on the sensor. To improve the performance of the sensor and reduce the prediction error of 3D forces, the BPNN optimized by a GA is built to realize the high-precision prediction of 3D forces. The average relative errors of F_x , F_y , and F_z predicted by the optimized BPNN are 13.8%, 5.9%, and 3.8%, respectively, that is, the prediction accuracies of F_x , F_y , and F_z are 86.2%, 94.1%, and 96.2%, respectively, which are much better than those without a GA optimization. The sensor proposed in this paper has advantages in sensitivity and structure, and it has particularly good practicability. The research provides both technical support and theoretical accumulation for the development of tactile sensing technology and artificial skin of robots.

Data Availability

The data used to support the study is available upon request to the corresponding author.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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