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Development of a polarization strain sensor system using a neural network

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We propose a polarization strain sensor system based on the principle that the polarization state of light propagating in a single-mode fiber changes when external strains change. We use a 3-layer feedforward neural network for data processing. Learning is performed by training a designed neural network using the experimental data as training data. In addition, the output obtained for the test data using the trained neural network is in good agreement with the experimental data used as the test data. This result demonstrates the feasibility of both the sensor system and data processing method.

1. Introduction

With the development of optical fiber sensing technology, optical fiber sensors have been fabricated for various applications, such as strain evaluation, health monitoring of buildings, aerospace technology, electric current measurement, and gas detection.[1-3] Optical fiber sensors are widely used because they have many intrinsic advantages, such as resistance to chemical corrosion, light weight, small size, remote sensing capability, immunity to electromagnetic interference, good corrosion resistance, and minimal electrical power requirements.[4-6] In addition, sensors that utilize the polarization characteristic of light propagating in an optical fiber have attracted substantial attention and been actively researched. Many excellent reports on polarization sensors have been published.[7-9] An all-fiber polarimetric strain sensor for composite structural health monitoring was proposed by Hegde and Asundi.[7] They discussed the application of the sensors in structural health monitoring of composites under static and dynamic loading. Dong and Tam proposed the first polarimetric fiber strain sensor based on a Sagnac birefringence loop.[8] The sensor system is temperature-insensitive and composed of an 8.6-cm-long polarization-maintaining photonic crystal fiber (PM-PCF). A few years later, Noh and Lee presented a temperature-insensitive polarimetric fiber strain sensor that uses a PM-PCF that is as short as 3.9 or 5.2 cm to achieve localized point sensing and sensor miniaturization.[9] However, the broadband light source and optical spectrum analyzer used in the experimental system made the sensor system expensive and large. Moreover, the PM-PCF and high-birefringent sensing fiber made the system costly and the operation difficult.

Neural networks have recently attracted substantial attention as they have many useful characteristics, such as learning abilities, nonlinearity, parallel processing, fast operation, and ease of implementation.[10-13] With these features, neural networks have been widely employed for various applications. They are used to solve a wide range of problems in signal processing, broadening measurement range, and development of intelligent optical fiber sensors.[13-15] Yang and Butler reported on a fiber-optic position sensor that used neural networks to process sensor signals.[13] Suah et al. presented an optical fiber pH sensor.[14] They used a feed-forward neural network to process the signal of the senor and successfully extended the response range of the sensor. An intelligent fiber optic sensor was proposed by Borecki.[15] The use of neural networks for signal processing made it possible to adopt elaborate constructions for specific measurements and made the sensor more accurate and universal.

In this study, we develop a compact and low-cost polarization strain sensor system. In the experiment, we use a conventional single-mode optical fiber wound in a coil shape as a sensor. The optical fiber can be purchased at a very affordable price in the market. When strains are applied, the sensor is rotated by the invar wire attached to the sensor. Then, we measure the change in the polarization state of the light reflected from a reflecting mirror that is connected to the back of the sensor when rotating the sensor. Since the polarization state of the light reflected from the reflecting mirror is measured, the light source and measurement device are located at the same end of the experimental system, thereby making the experiment easy to operate. In addition, owing to the laser diode light source and polarization analyzer that are used in the experimental system, the system can be built small. In addition, the sensor system we developed in this study is not affected by external temperature changes and does not require temperature compensation. To determine the strains applied in the experiment from the measured polarization state, we use a three-layer feed-forward neural network for data processing. The experimental data are used as training data for learning, that is, we take the measured polarization state as the input and the rotation angle (target output) of the sensor as the output for training the neural network. The output of the network is in very good agreement with the experimental data. In addition, to test the trained neural network, we provided a newly measured polarization state to the trained neural network. The output of the trained network, namely, the rotation angle of the sensor, is almost the same as the rotation angle applied in the experiment that generated the test data. Hence, the neural network has been satisfactorily trained. In addition, we performed a strain measurement experiment based on the measurement system, which is presented in another article.[16)] In that paper, we demonstrate that an arbitrary optical path can be computed with Jones matrices of two rotated wave plates. That is, when two Jones matrices that represent the optical path are obtained, the polarization state of the transmitted light can be calculated from that of the reflected light on this optical path and vice versa. The feasibility is also demonstrated by the experimental results. This computation will identify the effect of the former sensor on the latter sensor when a multipoint measurement is performed by connecting the sensors in series. Then, function fitting is used to obtain the rotation angle of the sensor from the polarization state; the errors between the angle that is applied in the experiment and the calculated angle are large. Moreover, when a multipoint measurement is performed by connecting sensors in series, the size of the experimental data becomes enormous and it will become very difficult to perform function fitting for data processing. Taking that problem into account, we decided to perform data processing using a neural network in this work. Using a neural network for data processing not only saves time but also improves accuracy.

2. Theory

2.1 Principle of the sensor

Since internal birefringence is induced when winding the fiber, the wound optical fiber can function as a phase plate. On the basis of this principle, a single-mode optical fiber wound in a circle is used as the sensor in this work, as shown in Fig. 1. The top and left-side views of the sensor used in the experiment are shown in Fig. 2. The sensor has the same effect as a rotated wave plate, and the phase difference δ can be calculated as:

$$\delta = \frac{2\pi}{m}, \qquad (1)$$

$$m = \frac{\lambda}{2\pi a r^2}\frac{R}{N}, \qquad (2)$$

where N is the number of turns of the fiber; r is the cross-sectional radius of the fiber; R is the bending radius of the fiber; λ is the wavelength of the laser light; and a is a calculable constant.[17)] As shown in Fig. 2, there is a base with a circular cylinder fixed to the center and a sector part with a groove fixed to the right side. Fibers wound in a circle around the cylinder are used as the sensor. When the invar wire attached to the sector part is pulled, the sensor rotates as the base rotates. When the sensor is rotated, the change in the polarization state of the reflected light from the reflecting mirror is measured. Then, we determine the rotation angle of the sensor from the measured polarization state. Therefore, when an object (e.g., buildings and slope) connected to the other end of the invar wire is deformed, the amount of strain can be obtained by this method. That is, when the object is deformed, the invar wire will be pulled, thereby causing the sensor to rotate. After obtaining the rotation angle of the sensor from the measured polarization state, we can obtain the amount of strain ε applied to the object from the rotation angle by a very simple mathematical transformation expressed as:

$$\varepsilon = \frac{\Delta L}{L}, \tag{3}$$

$$\Delta L = \pi R' \frac{\rho}{180}, \tag{4}$$

where ΔL is the moving distance of the invar wire, L $(1\ \mathrm{m})$ is the length of the invar wire, R' is the radius of the sector part, and ρ $(^\circ)$ represents the rotation angle of the sensor. [11)]

2.2 Numerical analysis

Recently, neural networks have been widely used to model human activities in many fields.[18-19)] Neural networks can learn from experiences and examples to identify the potential relationship between an input and the target output, which is a set of known values.[10)] Owing to their powerful function fitting capability, neural networks are widely used in data processing, because a feedforward neural network consisting of three layers, namely, one input layer, one hidden layer, and one output layer, can approximate any function with high accuracy.[19)] When using a neural network for function approximation, the input and the target output must be provided to the network. Such data pairs are called training data. Then, the neural network adjusts the internal parameters, namely, weights, so that the output of the neural network approaches the target output. When the learning is complete, the neural network has been trained and the weights have been corrected. When inputs other than training data are provided to the trained network, the neural network is expected to yield the correct prediction output.

3. Experiment and results

The experimental system is illustrated in Fig. 3, and a laser diode light source and a polarization analyzer are used. Since the objective is multipoint measurement, pulse light is used in the study. In the experiment, the wavelength of the light source is 1.55 μm, the pulse width of the light source is set to 3 μs, and the repetition frequency is 1 kHz. The maximum sampling frequency of the polarization analyzer is 1046 kHz. The pulse light from the light source passes through the polarization controller and is incident on the sensor via the optical circulator. The Fresnel reflected light, which is generated by the reflecting mirror and changes as the sensor rotates, is incident on the polarization analyzer through the optical circulator.

In the experiment, the sensor was rotated using the invar wire connected to the sensor from 0 to 180° in increments of 10°, while the linear polarizer (PL), the quarter-wave plate (QWP), and the half-wave plate (HWP) were all set to 0°. The changes in the polarization states of the reflected light when the sensor was rotated are shown in Fig. 4. The Stokes parameters S1, S2, and S3 represent the polarization states, which can be directly measured by the polarization analyzer in the experiment.

In this work, we use the experimental data shown in Fig. 4 as the training data for learning. The feedforward neural network we used is illustrated in Fig. 5. The learning method we used is error back-propagation.[20] Considering the time cost and accuracy, the number of neurons in the hidden layer is set to 10, with the neurons denoted as n_1, n_2, $\cdots$, and n_{10}. In Fig. 5, W denotes the weights, which are modified during the learning process. We provide the measured polarization states as input to the network and the rotation angles (target output) applied in the experiment are outputted by the network. A comparison between the angles outputted by the network and the angles applied in the experiment is shown in Fig. 6. According to Fig. 6, the angles applied in the experiment and the angles outputted by the neural network are in very good agreement. Relative errors are suppressed to 0.04% or less. The relationship between the angles applied to the sensor in the experiment and the measured polarization states was correctly determined. Moreover, the learning was performed correctly and the neural network was satisfactorily trained.

Furthermore, to test the trained neural network, we provided a newly measured polarization state to the network and calculated the angles. The comparison between the calculated angles and the angles that were applied in the experiment, which were used as test data, is shown in Fig. 7. As shown in Fig. 7, the angles applied in the experiment for the newly measured polarization states and the angles obtained using the trained neural network agree well with each other. The errors that occurred are not due to the poor performance of the experimental system, but to the experiments being conducted manually. Since the angles applied in the experiment and the calculated angles, which are shown in Fig. 7, are in good agreement, the measurement range was determined to be from 0 to 180°. Then, we calculated the strains using the rotation angles in the measurement range via Eqs. (3) and (4). The measurement range of strains that corresponds to the range of rotation angles is calculated to be 0-2.0×10^5 $\mu\varepsilon$. Hence, the strains can be accurately obtained by the proposed measurement method using the neural network.

4. Conclusions

In this paper, we propose a low-cost and compact polarization-type strain sensor system. For data processing, we use a 3-layer feed-forward neural network to approximate the relationship between the measured polarization states and the angles applied in the experiment. The calculated angles agree well with the angles in the experiment. Moreover, we calculated the angles for a newly measured polarization state with the trained network and obtained angles that are almost the same as the angles used as the test data applied in the experiment. Thus, it is possible to detect external strains using the developed sensor system and the neural network for data processing. Furthermore, we were able to perform multipoint strain measurements using the time delays of reflected pulses of a series of sensors with the system and neural network. In addition, the neural network could be used to overcome the difficulty of data processing as the number of sensors increases.

Acknowledgment

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Figure Captions

Fig. 1. Schematic diagram of the sensor.

Fig. 2. Top and left-side views of the sensor.

Fig. 3. Schematic diagram of the experimental system.

Fig. 4. Relationship between the polarization states and the rotation angles of the sensor.

Fig. 5. Feed-forward neural network used for learning.

Fig. 6. Rotation angles of sensor applied in the experiment and rotation angles outputted by the neural network for training data.

Fig. 7. Rotation angles of the sensor applied in the experiment and rotation angles outputted by the neural network for test data.

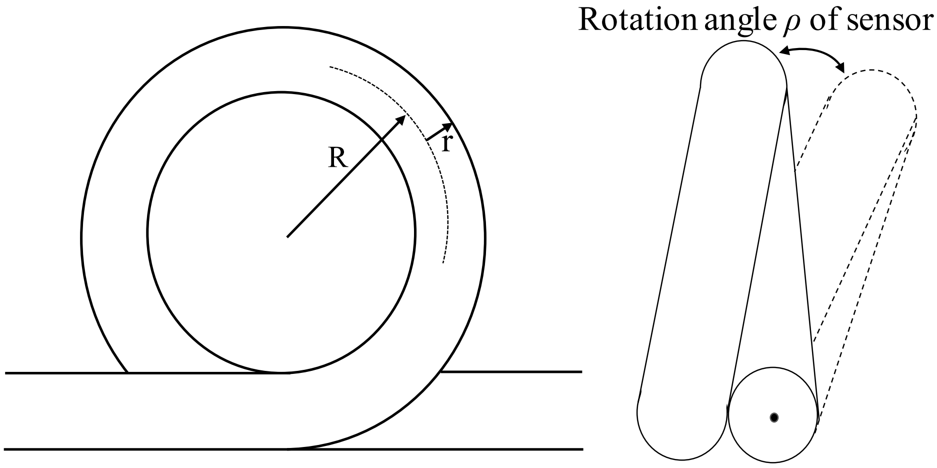


Fig. 1.

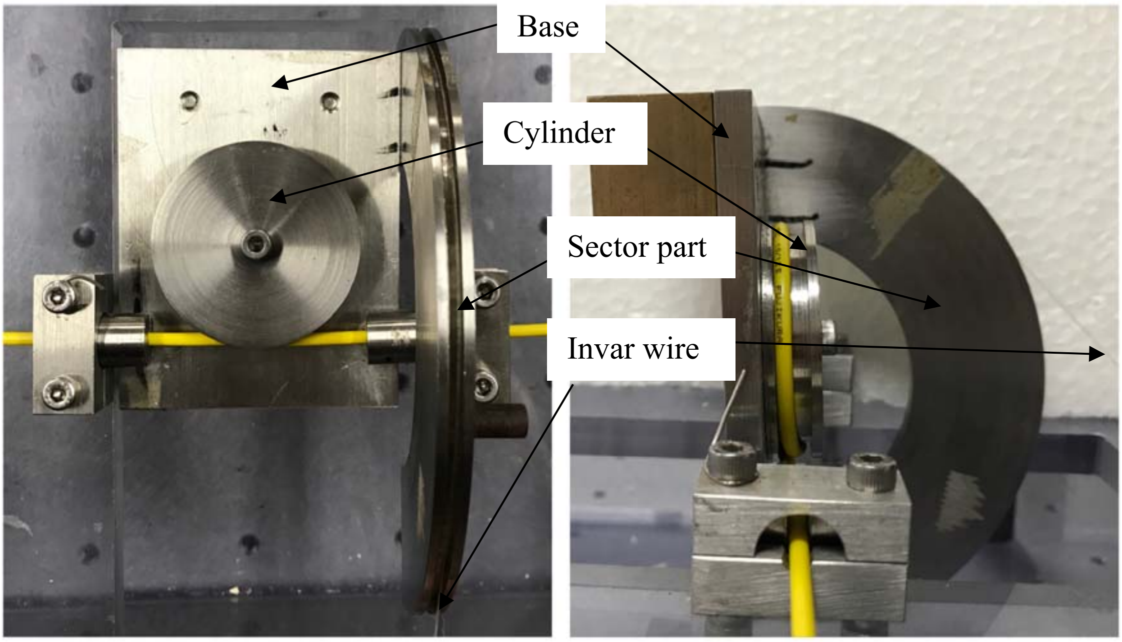


Fig. 2.

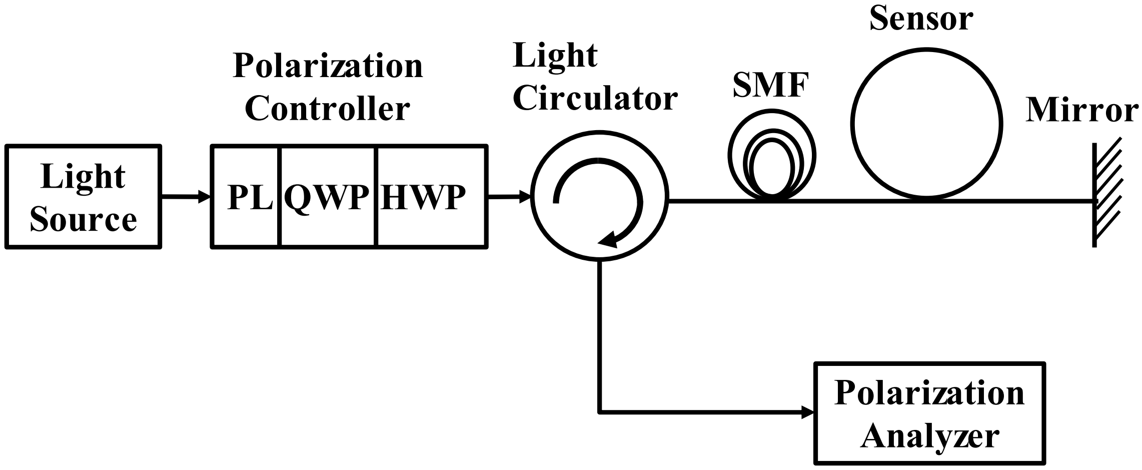
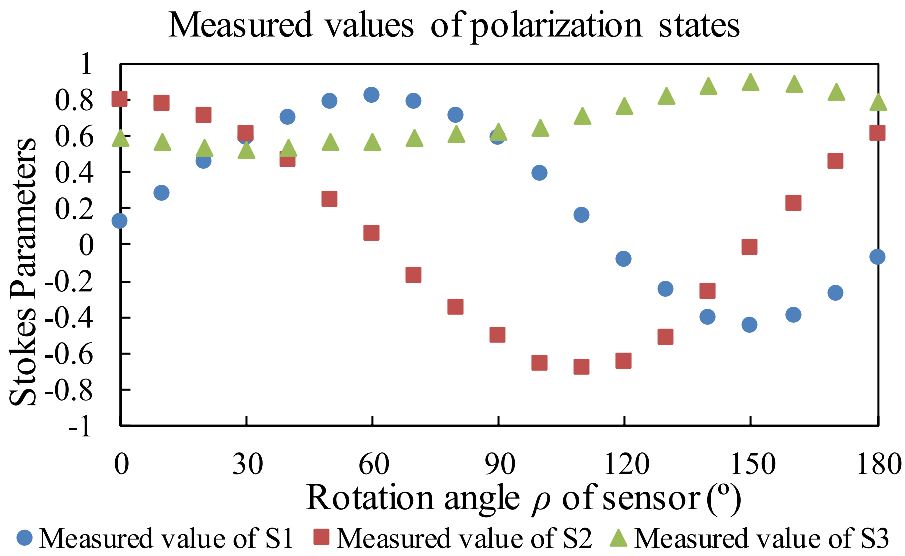
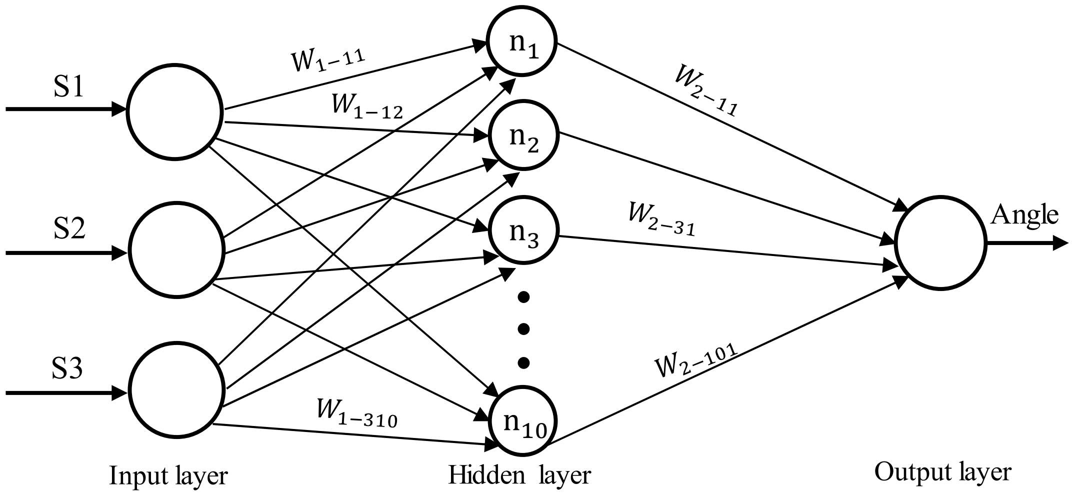

Light
Source
Polarization
Controller
PL
QWP
HWP
Light
Circulator
SMF
Sensor
Mirror
Polarization
Analyzer

Fig. 3.



Measured values of polarization states
Stokes Parameters
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0
30
60
90
120
150
180
Rotation angle ρ of sensor (º)
Measured value of S1
Measured value of S2
Measured value of S3

Fig. 4.



S1
S2
S3
W_{1-11}
W_{1-12}
W_{1-310}
n_1
n_2
n_3
n_{10}
W_{2-11}
W_{2-31}
W_{2-101}
Angle
Input layer
Hidden layer
Output layer

Fig. 5.

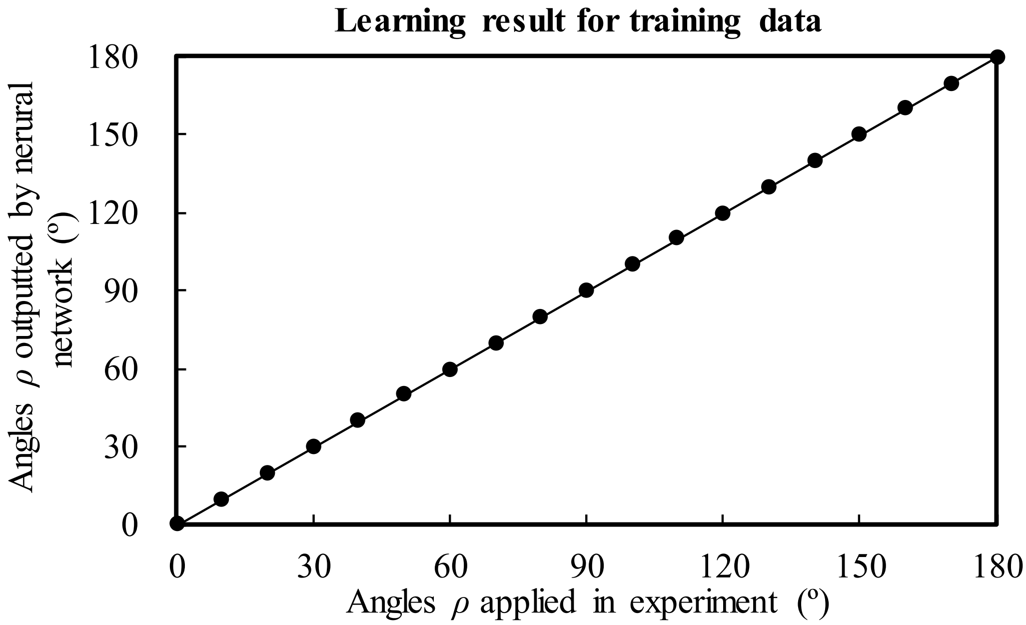
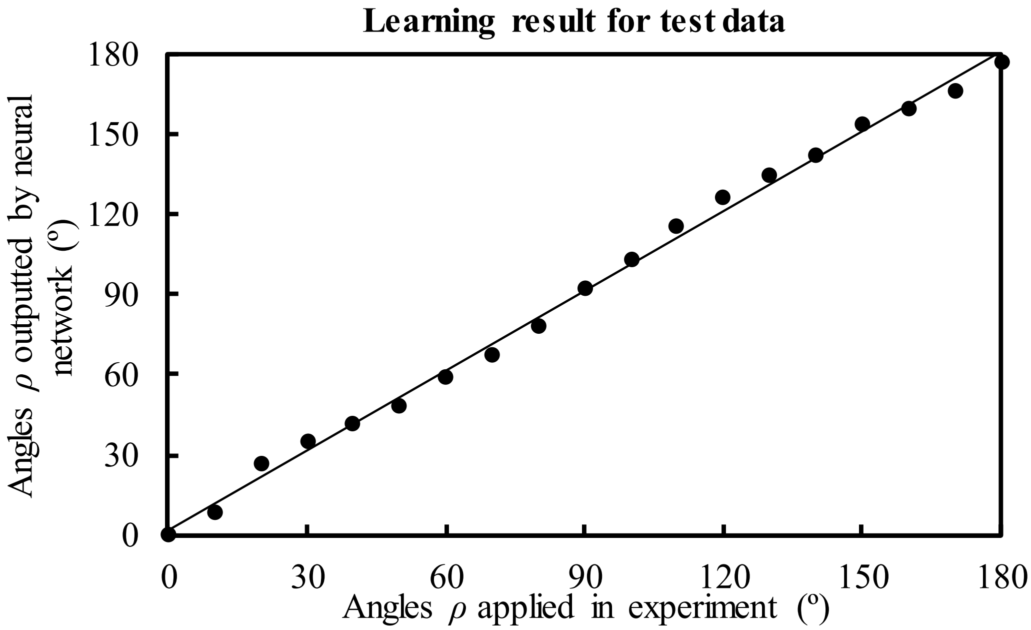

Learning result for training data
Angles ρ outputted by nerural network (º)
180
150
120
90
60
30
0
0
30
60
90
120
150
180
Angles ρ applied in experiment (º)

Fig. 6.



Learning result for test data
Angles ρ outputted by neural network (º)
Angles ρ applied in experiment (º)
0
30
60
90
120
150
180

Fig. 7.