A New 2D Displacement Measurement Method Based on an Eddy Current Sensor and Absolute Encoding

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Abstract: A new method of two-dimensional (2D) plane displacement measurement based on an eddy current sensor is proposed in this paper. A series of grooves with different widths and depths are engraved on the linear displacement table to form 2D absolute coding using the idea of pseudorandom coding. The eddy current sensor array is arranged above the groove to identify the coding. An artificial neural network is used to establish a measurement model which is the mapping relationship between the output of the eddy current sensor array and the 2D displacement of the workbench. A feasibility experiment showed that in the range of 20 × 20 mm, the root mean square error of measurement in the X- and Y-directions are 83 and 73 µm, respectively. The new method integrates eddy current sensor and artificial neural network modeling to realize 2D displacement measurement, which provides a new solution for displacement and angle measurement.

Keywords: eddy current effect; two-dimensional displacement measurement; artificial neural network

1. Introduction

In traditional boring, milling, and three-coordinate measuring machines, two guide pairs are generally arranged vertically to realize two-dimensional (2D) plane motion. This configuration does not conform to the Abbe principle. During the past two decades, the coplanar motion stage has attracted increasing attention with the development of micro-nano three-coordinate measuring machines, because this simplifies the structure and reduces the motion error source. More importantly, it conforms to the Abbe principle in the 2D direction, and its specific structure has various forms [1–4]. The measurement methods that matched the 2D coplanar motion stage mainly included dual-frequency laser interferometry and plane grating [5,6].

Existing plane 2D displacement measurement methods can be divided into two categories: optical and electricity methods [7]. The optical planar 2D displacement measurement method usually uses a pair of orthogonally mounted laser interferometers or linear encoders to realize large-distance measurements with nanometer resolution. Hsieh and Kuo proposed a heterodyne speckle interferometer for measuring the in-plane displacement of a 2D surface. Using the Doppler effect, the in-plane displacement of the surface will lead to phase change of the speckle interference pattern, from which the displacement information can be obtained. The resolution of the system reaches 1.5 nm [8]. Wu et al. proposed a new optical encoder which can independently and simultaneously measure in-plane and out-of-plane displacement. The symmetrical structure of the optical path can eliminate the influence of out-of-plane displacement on the in-plane displacement measurement. The nonlinearity error of the system reaches 7.06 nm [9]. In addition, the planar grating measurement system is also commonly used for displacement measurements. Zeiss has produced many mature planar grating products [10,11]. Liu et al. proposed a three-degree-of-freedom displacement measurement method for a planar mobile platform based on two planar gratings. Compared with the method using three one-dimensional linear...
gratings, the proposed method can reduce the coupling errors in the X- and Y-directions to 0.5 and 1.5 μm, respectively [12]. Lin et al. proposed a wide range of three-axis grating encoders with nanometer resolution which can simultaneously measure x-, y-, and z-axis translation motion. The z-axis displacement resolution of the grating encoder reaches 4 nm [13]. Optical planar 2D displacement measurement methods are characterized by high accuracy, however, they have poor environmental adaptability, such as poor resistance to oil and dust, as well as high vibration sensitivity.

The electricity planar 2D measurement method is divided into capacitance and inductance. The capacitive plane 2D displacement measurement method is mainly through the relative motion between the two plates to measure 2D displacement. Yu and Wang proposed a planar capacitance sensor capable of 2D large-scale measurement. The relative motion of the moving and the fixed plate changes the overlap area of the electrodes on these two plates, which causes periodic change in the capacitance to realize the measurement of 2D displacement. The resolution of the system is 0.308 μm [14]. Subsequently, the team also proposed a novel phase-shifting arctangent interpolation method to improve the measurement efficiency of the planar capacitive sensor, which can reduce the waveform error from 4% to 1.72% [15]. Capacitive displacement sensors can achieve μm- or even nm-level measurement accuracy in a small measurement range, but the dielectric constant between its two electrodes is easily affected by environmental factors, so capacitive sensors are not suitable for use in harsh environments. The inductive planar 2D displacement measurement method is mainly based on the principle of electromagnetic induction for 2D displacement measurement. Wu et al. proposed a novel inductive position sensor which can simultaneously measure the displacement in the X- and Y-directions. The sensor is composed of the ferromagnetic plate of the primary and secondary winding, composed of four-layer spiral coils. The maximum linearity within a spacing is 1% at 140 × 140 mm [16]. The team also proposed a new planar displacement sensor composed of primary and secondary coils. The primary and secondary coils are composed of a planar spiral coil array arranged in m × n and 2 × 2 matrices, respectively. The 2D displacement measurement is realized through the analysis and processing of the coil signal. In the range of 133 × 150 mm, the linearity of the X and Y are 0.37% and 0.27%, respectively [17]. The two-dimensional planar displacement measurement method based on inductive sensors can achieve high accuracy over a large measurement range, but its use of multiple inductive sensors in combination requires high parameter consistency of the sensors and high overall installation difficulty and cost.

In this paper, a new 2D displacement measurement method based on an eddy current sensor is proposed. Instead of the traditional displacement sensor, the current method uses the morphological characteristics on the surface of the coplanar 2D motion stage or intentionally graves or covers some geometric characteristics of the motion stage to realize the measurement. Thereby, the displacement measurement can be realized when, in some cases, the motion stage is not convenient to install the displacement sensor. This paper proposes a large-range, high-precision 2D plane displacement measurement method based on an eddy current sensor which has strong environmental adaptability and a simple measurement model, providing a new idea for the measurement of 2D plane displacement. From the feasibility experiment, this method has a certain application value.

The rest of the manuscript is structured as follows: Section 2 introduces the principles of the 2D displacement measurement. Section 3 discusses the simulation models and structural design. Section 4 discusses the feasibility experiments. Section 5 presents a summary and prospects of the measuring method.

2. Principle of Measurement

An eddy current sensor is usually used to obtain accurate size and distance following a change in sensor output voltage caused by back-electromotive force (EMF) generated by the eddy current effect [18]. The value of the back-electromotive force is directly related to the characteristics of the eddy current field generated by the metal. The contour of the
metal surface with different depths and widths can affect the eddy current field, which can lead to corresponding changes in the output voltage of the sensor. The team of the current study previously used this characteristic to achieve the identification of the spatial rotation direction of the spherical hinge and three-dimensional angle measurement by precisely cutting a series of grooves with different depths and widths on the ball head. This indicates that the proposed measurement method is feasible.

The measurement principle of the new method is shown in Figure 1. A series of grooves with different depths and widths are processed on a 2D working platform to form a 2D absolute coding using the idea of pseudorandom coding. The eddy current sensor array is arranged above the groove to identify this coding. When the platform moves in two dimensions, the output of the sensor array will change accordingly. By collecting the output of the sensor array and corresponding two-dimensional displacement, we can obtain the dataset of neural network training. Based on this, an artificial neural network is used to establish a measurement model which is the mapping relationship between the output of the eddy current sensor array and the 2D displacement of the workbench.

![Figure 1. Principle diagram of the 2D displacement measurement method.](image)

An RBF neural network is developed from multivariable function interpolation which simulates the neural network structure of the human brain with local adjustment and mutual coverage of the acceptance domain [19]. It is a feedforward neural network with local approximation performance. RBF can approximate any continuous function when there are enough hidden-layer neurons, that is, it has good global approximation performance. Its general approximation theorem [20,21] provides a theoretical basis for designing neural networks, and its topology is shown in Figure 2.

![Figure 2. Structure diagram of RBF neural network.](image)

When the radial basis function is selected as Gaussian function, the network output can be expressed as:

\[
y_i = \sum_{i=1}^{n} v_{ij} \exp\left(-\frac{1}{2\sigma^2} \|x_p - c_i\|^2\right) j = 1, 2, \ldots, n
\]

where \(x_p = (u_1^p, u_2^p, u_3^p, u_4^p, u_5^p, u_6^p, u_7^p, u_8^p)\) is the \(p\)-th input sample \((p = 1, 2, \ldots, p)\), \(p\) is the total number of samples, \(c_i\) is the center of the \(i\)-th Gaussian function, \(\sigma\) is the variance,
\( v_{ij} \) is the connection weight value from the \( i \)-th hidden layer node to the \( j \)-th output layer node, the total number of hidden layer nodes is \( h \), and the total number of output layer nodes is \( n \).

3. Simulation Analysis and Design

Through the above analysis, the new method needs to process grooves with different widths and depths on the 2D workbench so that it can perceive the change of groove parameters and output different voltage signals when the eddy current sensor sweeps through grooves with different widths and depths \[22\]. Finite-element analysis is conducted in this paper to explore the sensitivity of the sensor to the recognition of grooves with different widths and depths. A 3D finite-element model is established by using the AD/DC module of the COMSOL Multiphysics physical field simulation tool. The model details are shown in Table 1. Only three one-dimensional grooves are simulated in this paper to reduce the complexity of the model (Figure 3). A parameter difference was observed between every two grooves to simulate the influence of grooves with different parameters on the output of the eddy current sensor.

Table 1. Details of the simulation model.

| Parameter       | Value                      |
|-----------------|----------------------------|
| Plate size      | 50 × 100 × 5 (mm)          |
| Groove G1       | 20 × 3 × 0.4 (mm)          |
| Groove G2       | 20 × 5 × 0.4 (mm)          |
| Groove G3       | 20 × 5 × 0.2 (mm)          |

![Figure 3. The 3D finite element model.](image)

Grooves with different parameters are scanned by simulating eddy current sensors in the process of finite-element analysis, and the inductance changes of the sensor are recorded. Figure 4 shows that the inductance of the sensor will be significantly different when the sensor scans grooves with different parameters, and the difference is the largest especially when the sensor is located at the center of the groove. Simultaneously, Figure 4 shows that the sensitivity of the sensor to the groove depth is better than that of the groove width.

Figure 5 shows the inductance changes of the sensor continuously sweeping through three grooves. The diagram shows that the inductance changes are different, indicating that the sensor can identify the grooves when the sensor sweeps through grooves with different parameters. The output value will be different when the sensor sweeps through the grooves with different parameters, and these differences carry the corresponding position information.

Certain regularity should be given to the design of the groove through simulation analysis, combined with the idea of pseudorandom coding, because this paper uses artificial neural networks to fit the measurement model of sensor output array and 2D displacement. Combined with the size and range of the sensor, this paper makes the following design for the plate (Figure 6). The size of the metal plate, the width range of the groove, and the depth range are 115 × 130 × 10, 1–3, and 0.05–0.5 mm, respectively. The specific parameters are shown in Tables 2 and 3.
specific parameters are shown in Tables 2 and 3. (Figure 7). The output of the sensor changes with the displacement of the platform. The groove, and the depth range are 115 × 130 × 10, 1–3, and 0.05–0.5 mm, respectively. The analysis, combined with the idea of pseudorandom coding, because this paper uses artificial neural networks to fit the measurement model of sensor output array and 2D displacement. Combined with the size and range of the sensor, this paper makes the follow-ing information.

Figure 4. Sensors scan the inductance of grooves with different parameters. 

Figure 5. Inductance values of grooves with different parameters scanned continuously by sensors.

Figure 6. Flat physical map.
Table 2. Groove parameters in the X-direction (Starting from X = 0).

| Groove Number | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Width (mm)    | 1   | 2   | 3   | 1   | 2   | 3   | 1   | 2   |
| Depth (mm)    | 0.05| 0.10| 0.15| 0.20| 0.25| 0.30| 0.35| 0.40|

| Groove Number | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Width (mm)    | 3   | 2   | 3   | 1   | 2   | 3   | 2   | 1   |
| Depth (mm)    | 0.45| 0.50| 0.40| 0.30| 0.20| 0.10| 0.30| 0.50|

Table 3. Groove parameters in the Y-direction (Starting from Y = 0).

| Groove Number | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Width (mm)    | 1   | 2   | 3   | 1   | 2   | 3   | 1   | 2   |
| Depth (mm)    | 0.05| 0.10| 0.15| 0.20| 0.25| 0.30| 0.35| 0.40|

| Groove Number | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Width (mm)    | 3   | 2   | 3   | 1   | 2   | 3   | 2   | 1   |
| Depth (mm)    | 0.45| 0.50| 0.40| 0.30| 0.20| 0.10| 0.30| 0.50|

In this paper, the output of some areas of a single-sensor scanning plate is collected (Figure 7). The output of the sensor changes with the displacement of the platform. The output is different because of different groove parameters.

Figure 7. Output value of the single sensor in the range of 20 × 20 mm.

Based on the above simulation results and the actual sensor output value, it can be seen that the sensor output and displacement change is a nonlinear model. The sensor array is composed of multiple sensors. Due to the inconsistency of coding, each output of the sensor array corresponds to a 2D displacement. The powerful nonlinear fitting ability of the neural network is used to fit the corresponding nonlinear model to achieve the purpose of measuring 2D displacement.

4. Feasibility Validation
4.1. Establishment of Experimental Environment

The experimental device is shown in Figure 8. Two one-dimensional driving platforms are combined to form a 2D driving platform. The eddy current sensor is fixed by the magnetic table. A two-way drive is formed to realize the 2D motion of the flat plate relative to the sensor. A three-coordinate measuring machine is used to read the actual displacement to improve dataset accuracy. The range of the eddy current sensor (E202, Anhui Actus Technology Co., Ltd., China) is 0.6 mm. The temperature stability is 0.12 µm/°C. When collecting data, both x- and y-axes collect data from 0 to 20 mm with 0.5 mm intervals. Consequently, 1681(41 × 41) groups of data were collected. Due to the limitation of
conditions, the position of four sensors was changed and the above data acquisition process was repeated so that the output of eight sensors corresponds to the combination of 2D displacement \((U_1, U_2, U_3, U_4, U_5, U_6, U_7, U_8) \rightarrow (X, Y)\).

![Diagram of experimental setup](image)

**Figure 8.** Experimental installation, (a) Overall experimental environment, (b) Details of the experimental device.

### 4.2. Influence of Sensor Number on Accuracy

Based on experience, the data are divided into training (1600 groups), and test (81 groups) sets. The training set participates in network training. The test set is used to evaluate the advantages and disadvantages of the network models. This paper divides the number of sensors into five groups, i.e., 4, 5, 6, 7, and 8, to explore the influence of the number of sensors on accuracy, and conducts neural network modeling to compare the accuracy of the test set. The results are shown in Figure 9. The graph shows that the increase in the number of sensors is beneficial to the improvement of network accuracy. However, the accuracy of the improvement is limited when the sensor reaches >6. The specific results are shown in Table 4.

![Graph showing influence of sensor number on accuracy](image)

**Figure 9.** Influence of the number of sensors on accuracy, (a) X-direction, (b) Y-direction.

**Table 4.** Influence of the number of sensors on accuracy.

| Number of Sensors | Maximum Error in X-Direction (mm) | Root Mean Square Error in X-Direction (mm) | Maximum Error in Y-Direction (mm) | Root Mean Square Error in Y-Direction (mm) |
|-------------------|-----------------------------------|------------------------------------------|---------------------------------|------------------------------------------|
| 4                 | 46.92                             | 10.72                                    | 62.29                           | 12.01                                    |
| 5                 | 44.44                             | 9.33                                     | 39.33                           | 10.97                                    |
| 6                 | 3.16                              | 0.51                                     | 2.88                            | 0.42                                     |
| 7                 | 0.52                              | 0.17                                     | 1.02                            | 0.18                                     |
| 8                 | 0.47                              | 0.10                                     | 0.21                            | 0.08                                     |
4.3. Comparison of Several Neural Network Models

Combined with the previous experience and success of the team of this study, the obtained data are modeled based on BP, RBF, and ELM neural networks [23]. The output of eight sensors is used as the input of three neural networks, and the 2D displacement is used as the output of the neural network to establish three neural network models for comparison.

Based on the previous research on neural networks of our group, the three neural networks (BP, ELM, and RBF) selected in this paper are equivalent to other neural networks that are more conducive to the fitting and regression analysis of nonlinear models, and other neural networks such as convolution, recurrent neural networks, etc., play a greater role in image recognition classification and speech recognition [24]. The parameters of the three neural networks are shown in Table 5.

Table 5. The parameters of the three neural networks.

| Training Parameters | Type of Neural Network | BP | ELM | RBF |
|---------------------|------------------------|----|-----|-----|
| Activation function | $s(x) = \frac{1}{1 + e^{-x}}$ | $s(x) = \frac{1}{1 + e^{-x}}$ | $s(\|x - x_c\|) = e^{-\frac{\|x - x_c\|^2}{2\sigma^2}}$ |
| Number of hidden layers | 2 | 1 | 1 |
| Number of neurons | (21,7) | 1024 | 856 |

The results of the three networks are shown in Figure 10. The specific results are shown in Table 6. From Figure 10, it can be seen that the output curve of the BP neural network has the largest gap with the true value. Since the BP neural network has high dependence on the samples, the problem of gradient disappearance exists in this dataset, which leads to the failure of the learned model to reflect the real law inside the samples. Compared with the BP neural network, the accuracy of ELM neural network is improved. It is still weaker than the RBF neural network, due to ELM neural networks needing a lot of data support. As can be seen from the data in Table 6, the RBF neural network has the best performance and the highest accuracy.

Table 6. Influence of the number of sensors on accuracy.

| Network Model | Maximum Error in X-Direction (mm) | Root Mean Square Error in X-Direction (mm) | Maximum Error in Y-Direction (mm) | Root Mean Square Error in Y-Direction (mm) |
|---------------|-----------------------------------|------------------------------------------|-----------------------------------|------------------------------------------|
| BP            | 2.7807                            | 0.8359                                   | 3.1365                            | 0.8868                                   |
| ELM           | 0.4160                            | 0.1629                                   | 0.4309                            | 0.1737                                   |
| RBF           | 0.2782                            | 0.1060                                   | 0.2045                            | 0.0825                                   |

Figure 10. Comparison of three network models, (a) absolute error in X-direction, (b) absolute error in Y-direction.
4.4. Cross-Validation for Optimal Parameter Spread

The optimal spread value of the RBF network parameters is found by cross-validation. The root mean square error values in the X- and Y-directions are used as the evaluation criteria, and the spread is optimized from 0.5 to 2.5. The training and verification set divided by the previous data are combined and divided into 10 parts for cross-validation. The results are shown in Figure 11. The figure shows that the network output accuracy is highest when the spread is 1.

![Figure 11. Influence of spread value on network precision.](image)

4.5. Final Selection of Neural Network

According to the above analysis, the final network model selected in this paper is the RBF neural network. Based on this model, this paper randomly tests some points, and Figure 12 shows the test results. For the test set, the maximum error in the X-direction is 215.7 μm, and the root mean square error is 83 μm. The maximum error in the Y-direction is 271 μm, and the root mean square error is 73 μm. Specific data are shown in Table 7.

![Figure 12. Final test results, (a) absolute error in X-direction, (b) absolute error in Y-direction.](image)

| Network Model | Maximum Error in X-Direction (mm) | Root Mean Square Error in X-Direction (mm) | Maximum Error in Y-Direction (mm) | Root Mean Square Error in Y-Direction (mm) |
|---------------|----------------------------------|------------------------------------------|----------------------------------|------------------------------------------|
| RBF           | 0.2157                           | 0.083                                    | 0.2710                           | 0.073                                    |
4.6. Error Analysis

1. Regarding the quality of the dataset, although this paper uses the CMM to calibrate the displacement, it is inevitable that there will be noise interference, such as temperature drift of the eddy current sensor, the surrounding electric field, magnetic field, and some vibrations. This interference will cause the quality of the dataset to decline, and the neural network will fit a wrong surface due to the noise interference, which will lead to a reduction in generalization ability.

2. The number of datasets is not large, and the number of samples is a very important factor affecting the accuracy of the neural network model. The number of samples in this paper is 1681, which is still too small for a neural network, and will also cause insufficient generalization ability of the network.

5. Conclusions

In this paper, a new method of planar 2D displacement measurement based on an eddy current sensor and absolute encoding is proposed. The RBF neural network is used to establish the measurement model of the sensor array output and the 2D displacement of the 2D common free working platform, and the simultaneous measurement and positioning of the planar 2D displacement are realized. The feasibility of the method is verified by experiments. In the range of 20 × 20 mm, the linearity of X and Y is 1 and 1.3%, respectively. The root mean square error in the X- and Y-directions is 83 and 73 µm, respectively.

The new method integrates eddy current sensors and artificial neural network modeling to realize two-dimensional displacement measurement, which provides a new idea for free-scale measurement of displacement and angle measurement. The new method has good environmental compatibility, high precision, and fast dynamic response. Compared with the traditional multi-sensor modeling method, it simplifies the establishment of the measurement model and reduces the influence of processing technology on measurement accuracy. The new method is easy to install, flexible in measurement scheme, and fast in measurement speed. It is suitable for some harsh environments and is not easy to install with grating and other measurement occasions. It has popularization value in industry.

Due to temperature, vibration, and other surrounding environmental factors affecting the stability of eddy-current sensors, coupled with the shortcomings of neural networks easily falling into local optimal values, there is a lot of room for improvement in the accuracy of the new method, and measurement accuracy can be improved by enhancing the quality of the dataset (such as improving the data collection accuracy, increasing the dataset size, etc.), optimizing the coding method (simplifying the coding complexity, etc.), and selecting and optimizing the neural network algorithm (such as adding genetic algorithm, particle swarm optimization, and other nonlinear optimization algorithms).

Author Contributions: Conceptualization, writing—original draft, investigation, software, K.M. and P.H.; resources, experiment, data curation, Q.Y.; validation, formal analysis, J.Z.; writing—review and editing, X.D. and P.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grant 52175505.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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