Quantitative analysis of structural parameters importance of helical temperature microfiber sensor by artificial neural network

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ABSTRACT With the assistance of the evaluation algorithms based on the well-performed backpropagation neural network (BPNN), we quantitatively analyze the importance of the structural parameters of the helical microfiber (HMF) temperature sensor. The relative output intensities of HMF sensor at different temperatures are predicted by the BPNN with the structural parameters as the input variables. The best-forecasted performance is obtained by the BPNN with one hidden layer of ten neurons. Compared with the actual values, the root-mean-square error (RMSE) and the correlation coefficient of the predicted values are 9.7×10^-3dB and 99.84%, respectively. Based on the BPNN with precise prediction, the backward stepwise elimination and the holdback input randomization methods are used to quantitatively discuss the influence of the structural parameters on the output intensity of the HMF. The importance of four geometric parameters obtained by the two methods is ranked the same. The relative importance from high to low is the helical length (~38%), microfiber diameter (~27%), helical angle (~25%), and cone angle (~10%). Quantitative analysis of structural parameters relying on the well-predicted BPNN can give basic information on the structural characteristics of the HMF sensor, which helps to optimize the structure design of the optical sensors based on micro/nanofiber and provides a powerful guarantee for its practical application.

INDEX TERMS Helical microfiber, temperature sensor, quantitative contribution of structural parameters, backpropagation neural network

I. INTRODUCTION Optical sensors based on micro/nanofibers (MNFs), which have flexible and various sensing units, could provide high sensitivity and have become one of the most important applications of MNFs. In recent decades, a variety of sensing structures constructed by MNFs are proposed, from the simple geometry, such as biconical microfibers [1], [2] and U-type microfibers [3], to the delicate construction, for instance, gratings [4], interferometers [5] and coupled microrings [6], [7], [8]. When perceiving the same physical quantity, MNF sensors with different types of sensing units often obtain different optical signals and response relationships [9]. Meanwhile, even if the types of sensitive units are the same, there are some differences in the optical response due to the fabrication errors and geometric deformation of MNFs [10]. It has been shown that the optical properties of these MNF sensors are susceptible to their sensing structures. A deeper analysis of the structural characteristics should be carried out to improve the performance of the MNF sensors.

To discuss the impact of the sensing geometric parameters on the optical output, the single variable method is used to qualitatively analyze the experimental results of the MNF sensor with a simple structure [11], [12], [13]. However, for the MNF optical sensors with complex structures, the geometric parameters of the sensing unit are
abundant, and it is usually difficult to keep only one parameter fixed in the experiments. Besides, the structural parameters may relate to each other, such as the diameter and cone angle of a biconical microfiber [14]. Therefore, it is not possible to use the single variable method to estimate the importance of the parameters on the optical output. Moreover, the quantitative influence of a certain structural parameter on the optical output is even less likely to be achieved by traditional approaches.

Very recently, it has been reported that the artificial neural network can accurately predict the liquid concentration-light intensity response according to the structural characteristics of the MNF [15]. A large number of studies in other areas have shown that artificial neural networks can give the quantitative influence of each input variable on the output variable by the evaluation of network prediction effects [16], [17], [18]. This provides the possibility to investigate the quantitative contribution of sensing structure parameters on the optical output of the MNF sensor.

In this paper, we quantitatively analyze the influence of structural parameters on the output of MNF optical sensors using the backpropagation neural network (BPNN). A supported helical structure based on a biconical microfiber, which has several structural parameters, works as the working unit for temperature sensing. We establish the database containing the structural parameters and their working unit for temperature sensing. We establish the database containing the structural parameters and their corresponding temperature-light intensity data pairs, which are measured from 38 helical microfiber sensors (HMF). The BPNN with the structural parameters as the input variables is used to predict the outputs of the sensors at different temperatures. With the well-forecasted BPNN, we quantitatively compare the influences of the different structural parameters on the output of the sensor by the backward stepwise elimination method and the holdback input randomization method. Quantitative analysis of the structural parameters can provide a basis for evaluating the structural characteristics of the sensor, which could supply important information for designing MNF sensors and improving their performance in practical applications.

II. THEORY

A. SENSING CONSTRUCTION OF THE HMF TEMPERATURE SENSOR

The sensing unit of the HMF proposed here is made from a biconical microfiber with a cone angle of \( \alpha \) and a waist diameter of \( d \). As sketched in Fig. 1(a), the uncoupled microfiber is coiled along a metallic microrod with multiple turns (\( N \)) of equal distances. The helical length, which is the axial length of the coiled microfiber along the metallic microrod, is denoted as \( S \). The helical angle (\( \theta \)), which is related to the measured pitch (\( S/N \)) and the circumference of the microrod, could be calculated according to Fig. 1(b) by the equation in [19]. Considering the characteristics of the sensing structure, we use \( d, \alpha, S, \) and \( \theta \) as the basic structural parameters of the HMF sensor. \( N \) is the assisted parameter, which is used to increase the adjustment range of \( S \) in the experiments.

B. TOPOLOGICAL STRUCTURE OF BPNN

As described by [20], the topological diagram of BPNN in our work is depicted in Fig. 2. Between the two visible layers (Input layer and Output layer), several hidden layers with multiple neurons are introduced for the relative intensity prediction. Considering the output intensity of the microfiber is affected by the environmental temperature and the structural parameter of the sensing unit, we take and the geometric parameters of the HMF (\( d, \alpha, S, \) and \( \theta \) ) as the input variables besides the temperature (\( T \)). The output variable of the BPNN is the relative increment of the HMF transmission intensity (\( \Delta I \)). The measured data recorded from dozens of HMF sensors are used to train the network and predict the output intensity.
are employed to compare the prediction effect. The calculation expressions are as follows respectively:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2}
\]

(1)

and

\[
R = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}}
\]

(2)

where \(x_i\) and \(y_i\) are the actual and predicted intensity values of the temperature \(T_n\), respectively. \(\bar{x}\) and \(\bar{y}\) are the average values of the actual intensities and the predicted intensities in the range of the sensing temperatures. \(n\) is the total number of \(T-A\) data pairs obtained from one HMF sensor. The BPNN with smaller RMSE and larger \(R\) indicates a better prediction performance.

D. CALCULATION OF THE RELATIVE IMPORTANCE OF EACH STRUCTURAL PARAMETER

We use two methods to quantitatively analyze the degree of influence of the structure of the HMF sensor on its output. These two methods, which are based on the artificial neural network with good performance, have been widely recognized and successfully applied in many different areas [21]. Consequently, we employ them to evaluate the input neurons, i.e., the structural parameters of HMF in our study.

1. Backward stepwise elimination
   The backward stepwise elimination (BSE) is a method to obtain the importance of the input variables (the structural parameters of the HMF) by assessing the change of RMSE. We eliminate one input variable \(j\) at a time and predict the output parameter (the relative intensity of the HMF in our study). The corresponding RMSE\(_j\) is denoted as the predicting performance of the BPNN when the parameter \(j\) is removed [22]. The larger the RMSE\(_j\) is, the more important the corresponding input neuron \(j\) is.

2. Holdback input randomization method
   The holdback input randomization (HIPR) method is another widely used approach to deduce the importance of the input parameter in predicting the outcome. The values of one input parameter are firstly normalized and replaced by the random digits which are in the range of 0~1.0. Then the neural network is trained by the conventional process and used to predict the output parameter. The RMSE calculated from the predictive result is the evaluation index for the importance of the corresponding replaced input parameter. The larger RMSE indicates the more important of the corresponding input parameter. The detailed procedure of the HIPR method could be found in detail in [23].

3. Comparison of the two methods
   The above two methods can respectively measure the contribution of each input variable to the output variable. To compare these two methods, we calculate the relative importance of the neuron \(j\) (\(I_j\)) by the following equation [24]:

\[
I_j = \frac{RMSE_j}{\sum_{j=1}^{n} RMSE_j} \times 100\%, \quad j = 1, 2, 3, ..., n
\]

(3)
in which \(I_j\) is the contribution of the input variable \(j\) in the total contribution, \(RMSE_j\) is the predicting performance of the evaluated input variable \(j\) obtained by the BSE or the HIPR approach.

III. EXPERIMENT SETUP

The experimental setup is illustrated in Fig. 3. The HMF is assembled by wrapping a uniform waist of biconical microfiber (BMF) around a copper microrod. The diameter of the supported Cu microrod is 100 µm. The supported HMF is worked as the sensing unit and immersed into the Petri dish which is filled with water. The temperature of the water could be controlled by the heating plate under the dish and displayed by the thermometer in real-time. A broadband light source (400~750 nm) is launched into the HMF through the left standard optical fiber. The transmission signal is sent into a fiber optical spectrometer (Maya 2000pro, Ocean Optics) through the right standard optical fiber of the HMF. The temperature sensing process is monitored by a coupled charged device camera (CCD) which is mounted on an optical microscope.

FIGURE 3. Experimental setup of the HMF temperature sensor. Inset: typical optical microimage of the sensing unit of a HMF.

The inset image in Fig. 3 shows the typical sensing unit of a HMF. The three-turn HMF is made of an 11.0 µm diameter microfiber with a cone angle of 0.6°. The microfiber is coiled on the rod with a length of 4.71 mm. The helical angle of the HMF is 11.31°.
output angles are similar to each other (~35°) and fixed in our experiments.

We measured 758 T-ΔI data pairs from 38 HMF sensors fabricated by different BMFs. The distributions of the structural parameters of these HMFs are listed in Table 1. It could be seen that the BMF used to construct the sensor has a small cone angle and a long uniform waist diameter (usually a few micrometers).

**TABLE 1. Distributions of structural parameters of the HMFs in our experiments.**

| Structure parameter | Symbol | Range       | Mean value | Standard deviation |
|---------------------|--------|-------------|------------|--------------------|
| Diameter (μm)       | d      | 11.0~20.8   | 14.36      | 2.78               |
| Cone angle (°)      | α      | 0.6~1.9     | 1.22       | 0.59               |
| Helical length (mm) | S      | 3.11~7.77   | 4.95       | 1.05               |
| Helical angle (°)   | θ      | 5.30~11.93  | 9.51       | 2.40               |

The temperature range for sensing is from ~30 °C to ~70 °C. When the temperature is stable, several transmission spectra are recorded and averaged to eliminate the environmental disturbance. We take the averaged spectrum as the typical transmission spectrum under the temperature. Fig. 4 shows the typical spectra taken from the HMF of which the structural parameters are d=16.8 μm, α=0.6°, S=3.82 mm, and θ=9.3°. With the temperature increasing, the intensity of the transmission spectrum is growing, which could be seen more obviously in the enlarged area (the dashed rectangle in the main peak).

![Figure 4. The typical transmission spectra of the HMF sensor under different temperatures.](image)

Under each temperature t, we calculate the optical intensity (I_t) by summing the area of the entire typical spectrum and normalize it by the intensity taken at 30 °C (I_30°C). The relative transmission intensity (ΔI = 10lg(I_t/I_30°C)) of the HMF sensor is used to compare the changing degree of the output intensity with the temperature. Fig. 5 shows the comparison of the T-ΔI responses for the HMF and BMF sensors. The structural parameters of the HMF and BMF sensors are listed in Table 2. The BMF sensor (d=16.0 μm, α=1.0°, black circles in Fig. 5), which is a biconical microfiber suspended in the water without coiling and supporting, has a similar waist diameter and cone angle to the HMF1 (d=16.8 μm, α=0.6°, red circles in Fig. 5) and HMF2 (d=16.8 μm, α=0.6°, green circles in Fig. 5). For both the HMFs and the BMF, ΔI have linear increasing trends with the growth of the temperature. The increasing slopes of the relative intensities of the sensors indicate that the transmission loss is decreasing with the growing temperature [25,26].

**FIGURE 5. Normalized relative intensities of the HMFs and the BMF sensors with different temperatures.**

![Figure 5. Normalized relative intensities of the HMFs and the BMF sensors with different temperatures.](image)

To further compare the performances of BMF and HMF sensors, we linearly fit the response curve in Fig. 5 by the equation of ΔI=aT+b. The linear fitting coefficients (a) and correlation coefficients of the sensors are also shown in Table 2. It is found that the sensitivity of the BMF is 0.6×10^{-3}dB/°C, which is lower than that of the HMFs. Besides, the relative intensity data of the BMF sensor is more obviously scattered around the linear fitted line (black curve in Fig. 5). This indicates that the stability of the microfiber coiled on the copper rod is better than that of the BMF.

**TABLE 2. Structural parameters of the BMF and HMF sensors in Fig. 5.**

| Name   | d (μm) | α (°) | S (mm) | θ (°) | Sensitivity (a) (10^{-3}dB/°C) | Fitting correlation coefficient |
|--------|--------|-------|--------|-------|-------------------------------|-------------------------------|
| BMF    | --     | 16.0  | 1.0    | --    | --                            | 0.948                         |
| HMF1   | 2      | 16.8  | 0.6    | 3.82  | 9.3                           | 8.5                           |
| HMF2   | 2      | 16.8  | 0.6    | 6.77  | 5.3                           | 42.2                          |
As shown in Table 2, although the diameters and cone angles of the HMF1 and HMF2 are the same ($d=16.8 \ \mu m$, $\alpha=0.6^\circ$), the sensitivities of the two are quite different ($\Delta I_{HMF1}=8.5 \times 10^{-3} dB$/ $\Delta I_{HMF2}=42.2 \times 10^{-5} dB$/). This is mainly caused by the difference in the coiled density of the microfibers of the two HMFs. However, due to the structural correlation between $S$ and $\theta$ in the helical structure, it is hard to separate a single structural parameter and compare its influence degree on the sensor’s output. A similar situation also exists in the diameter ($d$) and cone angle ($\alpha$) of the microfiber [14],[27]. Consequently, it is quite difficult to carry out a systematic discussion on a single structure’s influence on the output of the sensor by using traditional approaches, let alone a quantitative analysis.

IV. UNITS RESULTS AND DISCUSSION

A. BPNN PREDICTION PERFORMANCE
To quantitatively analyze the relative importance of HMF structural parameters to $\Delta I$, an artificial neuron network with good performance should be established at the beginning. We use BPNN to predict the output intensities of the HMF. We randomly divided 758 pairs of measured $T-\Delta I$ data into two categories: the Training set and the Test set. The main parameters and settings used to train the BPNN, such as the activation functions of the input layer and the hidden layer, and the training function, are listed in Table 3.

| Model parameters & settings | Value/Name |
|-----------------------------|------------|
| No. of neurons in the input layer | 5 ($d, \alpha, S, \theta, T$) |
| No. of hidden layers | 1–2 |
| No. of neurons in the hidden layer | 3–12 |
| No. of training data pairs | 698 |
| Error goal | 1×10^{-3} |
| Training function | trainlm |
| Activation function for input-hidden layer | tansig |
| Activation function for hidden-output layer | purelin |
| Epoch (Iteration number) | 2000 |

To obtain the optimized network, we designed dozens of different BPNN structures by adjusting the numbers of the hidden layers and the neurons. The measured $T-\Delta I$ data pairs are selected from the Test Set and used to compare the performances of these BPNNs. The prediction performances given by these BPNNs are evaluated by RMSEs and Rs, which are listed in the Supplemental document (Tsi1). The best-performed BPNN, with one hidden layer of ten neurons, is marked by blue in Fig. 6. There is a large difference between the output intensities HMF1 and HMF3, which is mainly attributed to the differences in their structural parameters. The BPNN established before can obtain a good prediction of the $\Delta I$ in HMF1 (RSME=9.7×10^{-3} dB and R=99.84% for the HMF1). This indicates that the BPNN with one hidden layer of ten neurons performs well for the $\Delta I$-prediction of the HMFs with different structural parameters.

B. RELATIVE IMPORTANCE OF STRUCTURAL PARAMETERS OF HMF

To test the generalization ability of the BPNN, we selected another group of the measured data pairs (blue circles in Fig. 6) obtained from the HMF1. The measured $\Delta I$ and corresponding predicted values of HMF1 are marked by blue in Fig. 6. There is a large difference between the output intensities HMF1 and HMF3, which is mainly attributed to the differences in their structural parameters. The BPNN established before can obtain a good prediction of the $\Delta I$ in HMF1 (RSME=9.7×10^{-3} dB and R=99.84% for the HMF1). This indicates that the BPNN with one hidden layer of ten neurons performs well for the $\Delta I$-prediction of the HMFs with different structural parameters.

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method, while Fig. 7(b) shows the ones calculated by the HIPR method.

![Figure 7](image)

**FIGURE 7.** Importance of the structural parameters of the HMF sensor on the \( \Delta I \) prediction calculated by (a) BSE and (b) HIPR method. The error bar for each input variable is obtained by 50 times calculation. The length of the box represents the data ranging from 25% to 75%. The lines and squares in the box indicate the median and average values, respectively.

The largest average RMSE is obtained when we changed the values of \( S \), which are 7.27×10^{-2} \, \text{dB} \) by BSE method and 6.73×10^{-2} \, \text{dB} \) by HIPR method, respectively. This indicates that the axial length of the coiled microfiber along the metallic microrod has the greatest impact on the prediction accuracy of \( \Delta I \).

Meanwhile, the RMSEs of the other three structural parameters are different from each other. For the BSE method, the average values of RMSE corresponding to \( d \) and \( \theta \) are 5.42×10^{-2} \, \text{dB} \) and 4.92×10^{-2} \, \text{dB} \), respectively. When using the HIPR method, we obtained the average RMSE of \( d \) (4.68×10^{-2} \, \text{dB}) is close to the one of \( \theta \) (4.45×10^{-2} \, \text{dB}). The structural parameter that has the smallest values of the RMSE (1.94×10^{-2} \, \text{dB} \) by BSE and 1.69×10^{-2} \, \text{dB} \) by HIPR) is \( \alpha \). The results show that the influence of \( d \) and \( \theta \) on the prediction of \( \Delta I \) is significantly greater than that of \( \alpha \). This is mainly attributed to the structural property of the sensing unit. For the HMF sensor, the thinnest part of the microfiber waist is coiled on the microrod, which is used to sense the varying temperature directly. When the temperature is increasing, the deformation of the supported metallic rod caused by the thermal expansion leads to the tiny changing of \( d \) and \( \theta \). On the other hand, the tapered area of the microfiber was not wholly immersed in the liquid during the experiment, so that the influence of \( \alpha \) on \( \Delta I \) is minimal.

According to the average RMSE of each structural parameter in Fig. 7, we list the influence degree ranking of the structural parameters on \( \Delta I \), as shown in Table 4. Although the calculated processes of the BSE and HIPR methods are different, the rankings obtained from the two approaches are the same. The importance of the structural parameters that affect the network output, from high to low, is \( S, \, d, \, \theta, \) and \( \alpha \), respectively.

**TABLE 4. Rank for the relative importance of each structural parameter.**

| Variables | BSE | HIPR |
|-----------|-----|------|
| \( d \)   | 2   | 2    |
| \( \alpha \) | 4   | 4    |
| \( S \)   | 1   | 1    |
| \( \theta \) | 3   | 3    |

To quantitatively obtain the importance of structural parameters, we use (3) to calculate the relative importance of the structural parameter to \( \Delta I \). Fig. 8 shows the results of the two methods. The relative importance of helical length (\( I_S \)) is around 38%, which is the most important structural parameter that affects the change of light intensity. \( I_\alpha \) obtained by BSE or HIPR is less than 10%, which is the lowest among the four structural parameters. \( I_d \) and \( I_\theta \) are similar to each other and the relative importance of diameter (\( I_\theta > 26\%) is slightly higher than that of helical angle (\( I_\alpha \approx 25\%).

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which could provide important information on promoting their practical applications.

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