Capillary-Based Optical Fiber Sensor for Turbidity Measurement

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ABSTRACT

This work introduces an innovative capillary or hollow core-based sensor designed to measure turbidity by using the reflection of light in its cladding. The structure consists of two different capillary sections and has been optimized to maximise the interaction of light with the external liquid. Experimentation includes data collection from different turbidity levels using the reflected spectrum. To improve the measuring results, machine learning is implemented, exploring the effectiveness of various algorithms and neural network architectures to achieve a good root mean square error.

Keywords: Capillary, machine learning, optical fiber sensor, turbidity

1. INTRODUCTION

Monitoring water quality is essential in order to gain a deeper understanding and ensure the long-term preservation of aquatic ecosystems. In this context, fiber optics represent an innovative and ecologically friendly solution for measuring crucial parameters such as water flow, level, and turbidity. Turbidity is a critical factor in water quality assessment, and is used to quantify the cloudiness or haziness caused by suspended particles. The measurement is expressed in Nephelometric Turbidity Units (NTUs), which provides a standardized scale for assessing water clarity. This article concentrates on the particular use of fiber optics for measuring turbidity.

There are a number of commercially available turbidity meters on the market, with varying degrees of accuracy but some have measurement issues. Furthermore, these devices frequently have limited functionality. In light of these considerations, there is a clear need to develop new and improved sensors. Alternatively, optical fiber sensors are regarded as a new and suitable technology for these measurements. In this field, exist an infrared turbidity sensor for the aluminium sulfate coagulant process [1]. This pioneering approach demonstrated the potential of low-cost sensors to provide turbidity information with a maximum testing error of ±11.6% NTU. In the case of reference [2], a plastic optical fiber was used to assess the turbidity level. The sensor has been shown to be an effective and reliable means of measuring turbidity, achieving an R^2 value of 0.9947 in the best case.

This work introduces a new optical fiber sensor for turbidity measurement based on a multi-capillary structure. We have previously employed capillary structures for the measurement of strain, temperature and water level [3], [4]. Our sensor system has been designed to guide light along its cladding, facilitating interaction with the environment and making it ideal for use as a turbidity sensor. The measurement is performed in the sensor by capturing data in the reflected spectrum, with the results then compared with those from a commercial sensor in order to validate the NTU values. Given the lack of notable discrepancies in the raw data acquired from the various NTU levels, a classification approach was adopted utilizing machine learning. To this end, we have conducted a comprehensive study to determine the optimal neural network configuration using MATLAB and its Regression Learner application. The aim is to enhance the network's capacity for accurately classifying reflection spectra associated with different NTU levels, achieving an R^2 of 0.999 and a maximum error of ±5.21% NTU. This represents an improvement on previous studies in the field.

2. SENSOR DESIGN

The turbidity of a liquid is defined as its extinction coefficient due to light scattering. It can only be measured on the basis of this definition, i.e. optically [5]. In the majority of cases, light scattering from a turbid liquid is asymmetrical, with greater intensity observed in the forward direction than in the backward direction.

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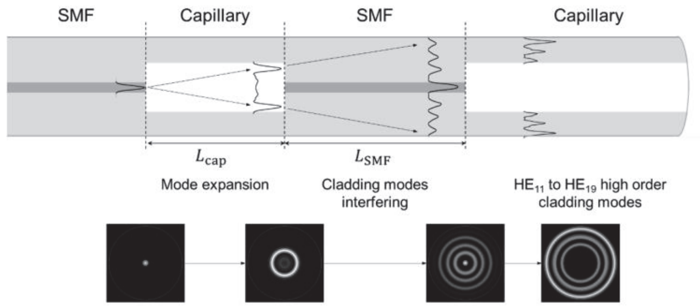

Figure 1. Schematic of the double SMF-HCF structure. The length of the elements is properly designed to provide controlled power transfer between the input SMF fiber mode and the highest possible order modes in the final capillary.

We have developed a fiber optic structure suitable for detecting variations of turbidity in water within the usual range of measurement in water quality applications. Our sensing transducer operates on the principle of light interaction with the surrounding medium - turbid water - as it propagates through the cladding of a capillary or hollow core fiber (HCF). To efficiently transfer light from a standard single-mode fiber (SMF) to the outer layer of the capillary fiber and to excite as many higher-order modes as possible, we propose and demonstrate the SMF-HCF structure shown in Fig. 1 The initial 55 µm diameter HCF fiber expands the incoming beam from the input SMF fiber to excite as many cladding modes as possible in the subsequent SMF section. These modes undergo multimodal interference, and with appropriate length, their field distribution allows effective coupling to the cladding of the final sensing HCF.

A commercial fully vectorial finite difference mode solver [6] was used to design the structure. Due to its symmetry, only radially symmetric modes were considered. The lengths of the intermediate capillary fiber (L_{CAP}) and the SMF (L_{SMF}) fibers (see Fig. 1) were carefully optimized to balance between transmitted power and the excitation of the highest possible order modes.

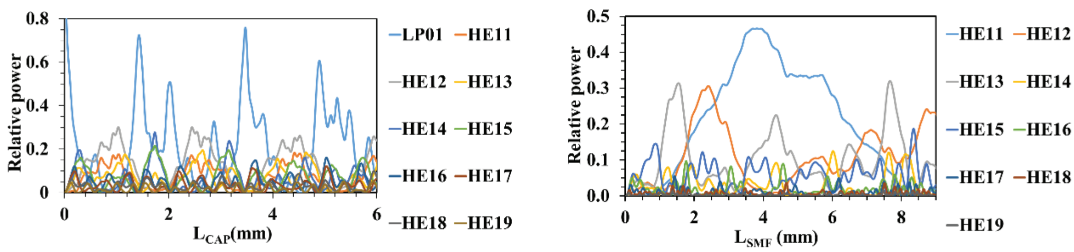

Figure 2. (left) Modal power distribution in the cladding of the intermediate SMF fiber caused by modal interference in the first capillary L_{CAP}. (right) Modal power distribution in the cladding of the sensing second capillary resulting from the modal interference in the intermediate SMF fiber L_{SMF}.

With regard to L_{CAP}, the study concentrated on identifying the points at which the guided mode (LP01) reached power minima and the higher-order cladding modes achieved power maxima (see Fig. 2 (left)). It was noted that at lengths of approximately 0.9, 2.5, and 4.5 mm, there were significant power minima in the guided mode and excitation of up to seven cladding modes, with minimal power loss (0.3 dB). To achieve an optimal balance between performance and ease of processing, the length of 4.5 mm was selected for L_{CAP}.

A comparable methodology was employed to ascertain the length of L_{SMF}, with an analysis of the power distribution across higher-order modes (up to the ninth order). At a length of 7.5 mm, there was a notable distribution of power into higher-order modes, resulting in a total insertion loss of 1.8 dB (see Fig. 2 (right)). This length was selected to optimise the effective modal coupling between the intermediate SMF and the sensing capillary.

3. DATA ANALYSIS

The objective of this experiment was to demonstrate the functionality of the fiber optic structure (Fig. 1) as a turbidity meter. In the manufacture of sensors, the Fujikura FSM-100P was employed, enabling the creation of different profiles through the modification of fusion parameters, thus allowing the fusion of diverse fibers, as HCF and SMF. The final capillary section was sealed using a last discharge of the Splicer, in order to avoid liquid in the hole of the last capillary.

Once the structure has been fabricated, a high-quality optical reflection signal is obtained using an FBG (Fiber Bragg Grating) optical interrogator (Micron Optics SM130). Fig. 3 (left) shows the reflected signal obtained from the structure, which exhibits the interference pattern predicted by theoretical calculations. This pattern is characterized by evenly spaced interference fringes, resulting from the constructive and destructive interference of light reflected between the structure's interfaces. It is observed a period of interference of 0.24 nanometers.
The structure was subjected to testing on the reflected spectrum as a function of temperature, with measurements taken at temperatures ranging from 27°C to 67°C. The maximum observed wavelength variation was 0.9 nm, a reduction in the signal level of approximately 40 a.u.

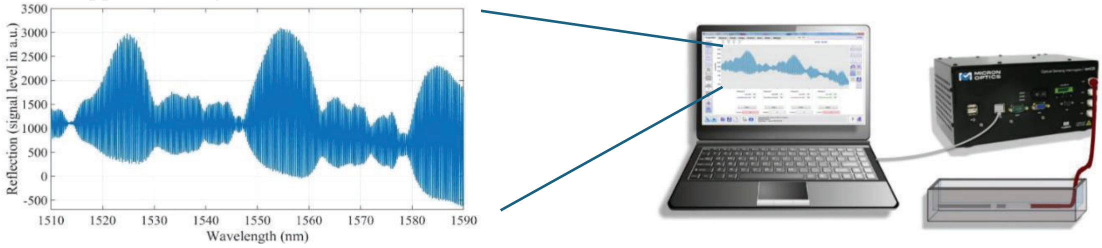

Figure 3. (left) Reflected spectrum from the multi-capillary structure. (right) Experimental Setup.

With regard to the experimental setup in the laboratory, a rectangular container with a thin profile was used to provide the required background to secure the fiber optic structure. Please refer to Fig. 3 (right) for details of the experimental setup. This allowed the container to be filled, enabling the fiber structure to be completely submerged in each of the liquid solutions, each with a different NTU value. To create different levels of turbidity, ultrapure water was used as a base and formazin was added. Formazin is directly correlated with turbidity variations. Measurements were taken for each distinct liquid solution, spanning a range from 0 to 280 NTU at 40 NTU intervals. To verify that the solutions reached the desired NTU levels, a commercial turbidity meter was used [7].

The initial analysis shows a wavelength shift of the transfer function depending on the formazin concentration. But we obtain inconclusive findings when we try to relate the turbidity with just one parameter (see Fig. 4 (left)). Fortunately, today we can use techniques that help us to make measurements in these complex scenarios. So, we opted to analyse the received reflected spectrum using machine learning for data classification. In particular, the MATLAB Regression Learner tool [8] which provides an intuitive interface for building and evaluating regression and classification models. This application identifies patterns and relationships between features and the target variable.

To assess the model's predictive performance, a five-fold cross-validation approach was employed. This involved splitting the dataset into five parts, ensuring that each part served as both training and validation data. This process reduced bias and provided a robust estimate of the model's accuracy, with the root mean square error (RMSE) being the key metric for comparing model performance. The turbidity measurement dataset, which was originally limited in scope, was augmented by generating "pseudo samples" through the addition of Gaussian noise [9], thereby expanding the dataset to 120 samples. A variety of machine learning models were trained. Neural networks, in particular two-layer (Bilayered) and three-layer (Trilayered) models, demonstrated consistent superior performance compared to other models.

Table 1. Comparison of RMSE across various neural networks over 20 iterations: analysis of average, median and variance to assess consistency and performance.

	RMSE				
NEURAL NETWORKS	NARROW	MEDIUM	WIDE	BILAYERED	TRILAYERED
Average	4.21	4.17	4.21	3.75	3.66
Median	4.25	4.13	4.18	3.75	3.61
Variance	0.05	0.03	0.04	0.05	0.05

Table 1 provides an overview of the average, median, and variance for all cases of neural networks in 20 iteration of training. Is Trilayered Neural Network that consistently exhibits the lowest RMSE values across all iterations, indicating superior overall performance (the lowest value obtained is 3.27). Furthermore, a graph illustrating the correlation between the predicted and true responses confirmed the high accuracy of the trilayered neural network, with a slope of 0.999, indicating near-perfect alignment between the two values. The model demonstrated an excellent level of accuracy in predicting turbidity levels, with a maximum testing error of 5.21% NTU and a median error of 2.19%. The model's practical utility was further enhanced by MATLAB's capability to export trained models for real-time application. This included the option to integrate with the Micron Optics sm130 interrogator to process spectral data and predict turbidity in real time.

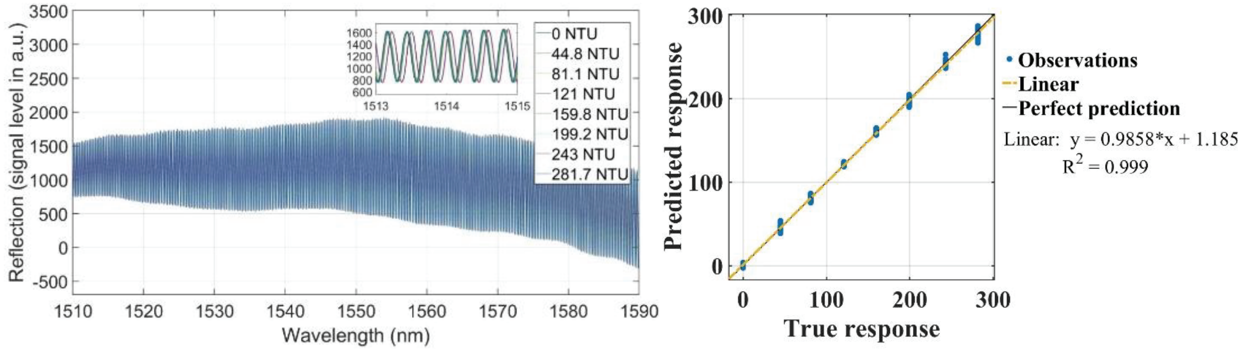

Figure 4. (left) Reflected spectra from the multi-capillary structure immersing in liquid with different values of NTU. (right) Best value of RMSE obtained, model Trilayered Neural Network.

4. CONCLUSION

In conclusion, this study demonstrates the viability of using a multi-capillary sensor optimised for turbidity measurement through light reflection from the sensor's cladding and employing machine learning to analyse the reflected data, which has significant potential for use in a range of applications. The sensor´s structure is designed to optimise power transfer between the input fiber core modes and the highest-order cladding modes in the final capillary. The three-layer neural network proved to be the most effective, achieving a maximum testing error of 5.21% NTU. This highlights the potential of this technology to improve water quality monitoring and management in a variety of applications.

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