Toward a multipoint optical fibre sensor system for use in process water systems based on artificial neural network pattern recognition

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Toward a multipoint optical fibre sensor system for use in process water systems based on artificial neural network pattern recognition

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Abstract: An optical fibre sensor capable of detecting various concentrations of ethanol in water supplies is reported. The sensor is based on a U-bend sensor configuration and is incorporated into a 170-metre length of silica cladding silica core optical fibre. The sensor is interrogated using Optical Time Domain Reflectometry (OTDR) and it is proposed to apply artificial neural network (ANN) pattern recognition techniques to the resulting OTDR signals to accurately classify the sensor test conditions. It is also proposed that additional U-bend configuration sensors will be added to the fibre measurement length, in order to implement a multipoint optical fibre sensor system.

1. Introduction

The main drive of the present research in the area of optical fibre sensors in the water industry is to produce a range of optical fibre based sensing techniques, preferably on a single optical fibre, which can be used for a variety of different sensing purposes and at the same time compete with existing conventional sensing methods. Optical fibre sensors also have a series of characteristics that are familiar: they are compact, lightweight and in general minimally invasive, as well as offering the prospect of multiplexing numerous sensors effectively onto a single fibre network. However, all should be immune to electromagnetic interference as there are no electric signals present in the vicinity of the sensing points. These properties, along with their capability for distributed or multipoint sensing, allow for the development of reliable and cost effective sensor systems that can be used in a wide range of application areas.

In this investigation, an evanescent field optical fibre sensor has been incorporated into a 170m length of 62.5µm core diameter silica clad silica (SCS) core optical fibre. A 3cm section of the optical fibre’s buffer and cladding are removed and the core of the optical fibre is exposed directly to a measurand. In order to maximise the sensitivity of the sensing region of the fibre, a U-bend sensor configuration is utilised to increase the evanescent field penetration at the sensing region [1]. This is an advancement on work previously reported by King et al [2], which was based on polymer clad silica (PCS) fibre in which the system attenuation losses were higher. With the reduced losses of the present system, the optical power budget available is capable of incorporating more sensors than previously implemented used on PCS fibre. The interrogation of such a sensor system uses an established technique known as Optical Time Domain Reflectometery (OTDR), which was first reported by Barnoski and Jensen in 1976 [3].
Optical fibre sensor signals can often be complex and cross coupling of signals from external parameters, e.g. temperature (the true measurand) and strain or microbending (interfering parameters in this case), adds to the difficulty interpreting data from such systems. It has been proposed that for many applications of optical fibre sensors, artificial neural network (ANN) pattern recognition techniques may be used to resolve the problems arising from cross-sensitivity to other parameters [4].

Previous work by King et al has demonstrated the ability of ANN pattern recognition techniques to accurately classify sensor test conditions on both single point and multipoint [2] optical fibre sensor systems for environmental monitoring purposes. In this investigation, ANN pattern recognition techniques are coupled with signal processing techniques, based on the Discrete Fourier Transform (DFT), in order to accurately classify the sensor’s test conditions. Test results for sensor immersion in water and exposure to air are initially presented, followed by sensor exposure to various concentrations of ethanol in water.

2. Experimental Set-Up

In this investigation the sensor was incorporated into a 170m length of 62.5µm SCS optical fibre. The optical fibre used was a 62.5µm/125µm core/cladding graded index fibre (Product no.: €F G62.5/125), supplied by ART Photonics. In order to maximise sensitivity, a U bend configuration was used for the sensor where the cladding was removed and the core exposed directly to the measurand. The operation of the sensor is based on direct modulation of the light intensity propagating in the fibre by the measurand, as a result of the interaction with the evanescent field penetrating into the absorbing measurand. Much experimental work has already been reported [5] for a single U-bend sensor detailing resulting sensitivity gains from evanescent wave increases from the curving of the sensing fibre. It has been shown by Gupta et al that the sensitivity of the sensor increases with decreasing bend radius of the probe and also with the increase in refractive index of the fluid under test [5].

3. Sensor Fabrication

The first stage in the fabrication of the U-bend sensor is to remove the buffer from a 3cm section of the optical fibre. The prescribed 3cm section was soaked in acetone for 60 minutes and the buffer was then carefully removed using a 203µm fibre-stripping tool. In order to shape the fibre to the desired sensor configuration, the exposed fibre was cleaned using acetone and was then slowly bent into a U shape using heat from a flame. The bending procedure was controlled using an in house developed fixture to improve the repeatability of the sensor manufacturing. This technique is described in detail in previous work by King et al [2].

The final stage of the sensor fabrication was the chemical removal of the silica cladding from the fabricated U-bend sensor. This was achieved by etching the sensing tip of the U-bend sensor in a buffered hydrogen fluoride (BHF) solution. The use of the BHF solution to remove silica cladding from an optical fibre has been previously documented for numerous sensing applications [6]. BHF consists of 50% weight hydrofluoric acid (HF), 40% aqueous solution of ammonium fluoride (NH₄F) and distilled water (DH₂O). The volume ratio of the BHF solution in this investigation comprised 40% NH₄F : 50% HF : DH₂O at 2 : 1 : 1. The etching procedure was performed under chemical fumehood conditions and the temperature of the etching solution BHF was maintained below 27 °C. The optimum time required to successfully remove the 125µm silica cladding was found to be 102 minutes. A photograph and a schematic of a fabricated U-bend
sensor are shown in figure 1. The fabricated U-bend sensor was examined using a scanning electron microscope and was observed to have a bend radius of 0.977mm.

![Fabricated U-bend Sensor](image)

**Figure 1.** Fabricated U-bend Sensor

### 4. Measurement System Configuration

The system configuration for this investigation is shown in figure 2. It comprises the optical fibre sensor, an EXFO IQ7000 (0.85 µm) OTDR and a Pentium MMX 200 MHz PC running LabVIEW Virtual Instrument (VI) programs for data capture and pre-processing. The LabVIEW VI programs were developed by the authors specifically for this investigation, and the resulting data output were made available for analysis by the signal processing technique and the ANN implemented using SNNS V4.1.3 (Stuttgart Neural Network Simulator) [7].

![Measurement System Configuration](image)

**Figure 2.** Measurement System Configuration

### 5. Results

In order to train and test an Artificial Neural Network (ANN) pattern recognition system, it is necessary to obtain a large number of patterns. Numerous OTDR readings, each of three minutes duration, were taken for each of the sensing conditions under test as shown in table 1.

| Sensor Test Condition | Number of OTDR Readings |
|-----------------------|-------------------------|
| Air                   | 140                     |
| Distilled Water       | 140                     |

**Table 1a.** Sensor Test Conditions Investigated 1: Air and Distilled Water

| Sensor Test Condition | Number of OTDR Readings |
|-----------------------|-------------------------|
| 12.5% Ethanol         | 75                      |
| 25% Ethanol           | 75                      |
| 50% Ethanol           | 75                      |

**Table 1b.** Sensor Test Conditions Investigated 2: Various Ethanol Concentrations
The sensing area of interest on the OTDR trace forms a relatively small part of the overall trace (approx. 300 points out of a total of 7,300, figure 3) and therefore to maximise efficiency of the computer algorithm, it was necessary to design an in-house LabVIEW VI that would locate the sensor peak, select the required window width and save this data for analysis by the signal processing and the SNNS software. A typical output measurement trace obtained from the OTDR when the sensor is exposed to air and immersed in distilled water is shown in figure 4a. Figure 4b shows the sensor response to immersion in the various concentrations of ethanol listed in table 1.

6. Signal Processing Analysis

It can be observed from the extracted OTDR peaks shown in figure 4, that it is relatively low frequency information that is of interest in this classification. Due to the low frequency nature of the information, a discrete Fourier transform (DFT) using an FFT algorithm can be directly applied to the OTDR peaks without having to apply any windowing transform. The low frequency nature of the information also reduces concerns over filtering and aliasing in the frequency domain. Prior to application of the signal processing analysis, the OTDR sensor data is normalised between +1 and –1 using the standard LabVIEW Scale 2D array VI. The signal processing analysis in this investigation is performed using an in house developed MATLAB program. Once the extracted OTDR sensor peaks are inputted into MATLAB, a 512-point DFT of the peak is calculated using an FFT algorithm and from the resulting Fourier transform the power spectral density (PSD) of the OTDR output is calculated.
The resulting PSD plots are shown in figures 5a and 5b, for each of the sensor test conditions. As anticipated, the main PSD area of interest is located in the low frequency region. As a result of the application of the discrete Fourier transform, the OTDR peak information is now more explicit and easier for the user to access in comparison to time-domain based results which require all of the extracted OTDR peak data points.

7. Artificial Neural Network Pattern Recognition

In order to perform the ANN pattern recognition analysis for sensor exposure to air and immersion in water, a three-layer feed-forward ANN was implemented in the SNNS software package. The ANN consists of a ten node input layer, to represent the PSD traces of the OTDR signals, a four node hidden layer and a two node output layer, the latter containing one node to represent each of the sensor’s test conditions. In order to determine the optimal size of the ANN hidden layer, numerous trials with hidden layers of two nodes up to six nodes were performed. It was observed empirically that a hidden layer of four nodes performed best in this investigation.

The application of the DFT based signal processing analysis has been successful, as it has reduced the size of the input (and hidden) layers required to accurately represent the OTDR output data. The extracted OTDR sensor peaks contained approx. 300 data points, which would have led to a large number of nodes on the implemented ANN’s input layer, whereas the resulting PSD trace can accurately represent the OTDR data with just ten input layer nodes.

A total of 200 result patterns were used to train the network – 100 for each condition listed in Table 1a. For the purpose of training the feed-forward network, 10 cycles were required using a back-propagation algorithm. The algorithm used in this classification is listed in the SNNS learning functions as BackPropMomentum. The network was initialised with randomised weights and trained with a “topological order” update function [7]. In order to test the operation of the trained network, an independent set of data to those that had been applied in the training of the network was used. This was generated from the remaining unused 40 result patterns for each condition listed in table 1a, 20 for each test condition. The resulting 40 patterns were applied to the trained network and were all classified correctly. Table 2a shows a sample of the results obtained when the test patterns were applied to the trained network.

| Sensor Test Condition | Test Patterns | Expected Output | Observed Output |
|-----------------------|---------------|-----------------|-----------------|
| Air                   | 20            | 0 1             | 0.014 0.992     |
| Distilled Water       | 20            | 1 0             | 0.901 0.099     |

Table 2a: ANN Analysis Test Results: Exposure to Air and Immersion in Distilled Water
The ANN analysis procedure was then repeated for the results based on the sensor’s exposure to various concentrations of ethanol. The ANN implemented in SNNS to perform this task comprised an input layer of eight nodes, a hidden layer of two nodes and an output layer of three nodes, one node to represent each of the sensor test conditions. A total of 180 result patterns are used to train the implemented ANN, 60 patterns for each of the sensor test conditions listed in table 1b. A back-propagation algorithm was used to train the ANN and 500 cycles were required for the ANN to train successfully. The remaining 45 result patterns were then used to test the operation of the trained ANN. Fifteen patterns for each of the sensor test conditions were applied to the trained ANN and each pattern was classified correctly. Table 2b shows a sample of the ANN test output classifications.

| Sensor Test Condition | Test Patterns | Expected Output | Observed Output |
|-----------------------|---------------|-----------------|-----------------|
| 12.5% Ethanol          | 15            | 0 0 1           | 0.038 0.012 0.931 |
| 25% Ethanol            | 15            | 0 1 0           | 0.073 0.961 0.090 |
| 50% Ethanol            | 15            | 1 0 0           | 0.915 0.057 0.021 |

Table 2b: ANN Analysis Test Results: Exposure to Various Concentrations of Ethanol

8. Conclusion and Future Work

A reliable optical fibre sensor for use in process water systems has been described. OTDR has provided a successful method for interrogating the sensor and by using a U-bend sensor configuration, the sensitivity of the sensing region has been greatly increased. From the results obtained in table 2, it can be seen that both the DFT based signal-processing analysis and the ANN pattern recognition techniques have achieved their aims. The ANN implemented in SNNS has trained successfully and accurately classified each of the sensor test conditions while the DFT based signal processing has minimised the computational resources of the ANN in SNNS, without affecting the accuracy of the ANN classifications.

The improved power budget arising from this sensing configuration (compared with work performed on PCS fibre [2]) makes it possible to add further sensors onto the fibre length in order to implement a multipoint optical fibre sensor system for use over a long distance. The experimental setup and sensor fabrication techniques detailed in this investigation to date guarantee a repeatable method for fabricating U-bend sensors and further sensors may be added by using fusion splicing and longer fibre lengths than described.

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