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Research on Multi-scale MLSTM Integrated Detection Algorithm for Fiber Raman Temperature Measurement

Hongbin Sun[1, a, *], Tianyu Li[1]

[1]School of Electrical Engineering, Changchun Institute of Technology, Changchun, China.

[a]Win_shb@163.com

Abstract

The core problem of improving the resolution of the distributed optical fiber temperature measurement system is the signal processing method. For high frequency bandwidth and attenuation of the information, automatic detection is very difficult. In this paper, a Fiber Raman Temperature Measurement detection algorithm based on multi-scale MLSTM integrated model is proposed. The algorithm firstly uses wavelet analysis method to process the signal, and then obtain wavelet processing results in various scales. A multi-scale hierarchical structure MLSTM is constructed which can be used to discover the deep characteristic information of the traveling wave, and obtains a novel detection model. The experimental results show that the proposed method improves the stability and accuracy compared with the traditional algorithm, and the method has good practical value.

Keywords

Deep learning, MLSTM, Fiber Raman Temperature Measurement, Neural network.

1. Introduction

The distributed fiber temperature sensing technology based on the fiber Raman scattering effect has been widely used, and combined with new signal acquisition and processing technology and networking technology, it has better results. However, there is no effective solution to the important problem of weak optical signals and noise signals in distributed optical fiber Raman temperature sensing systems, for weak temperature signals are completely obliterated by noise signals. The acquisition has a low signal-to-noise ratio. There must be efficient processing algorithms.

In the process of wavelet transform de-noising, wavelet analysis can be used for multiple time windows and frequencies. During wavelet multi-scale analysis, high-frequency noise will rapidly decay with the wavelet transform coefficient modulus maximum, which is the advantage of over other methods [1, 2]. However, wavelet analysis needs to choose the type of wavelet base and the decomposition scale. This choice also will have a huge impact on the results [3]. After signal processing, the current research mostly uses support vector machines, neural networks, and decision trees to analyze the data to obtain an automatic identification model, and the ability to use the model to implement automatic wave detection [4,5]. In order to solve the related problems, this paper proposes a travelling wave head detection algorithm based on Multi-scale MLSTM integrated model (TWH-M-MLSTM). The algorithm first uses wavelet analysis to process the signal. Processing to obtain the wavelet processing results at various scales; after processing, a multi-scale hierarchical MLSTM model was constructed to discover deep characteristic information. The method proposed in this paper introduces multiple sets of scales and parameters at the same time and uses the decision integration method to obtain the final result. The experimental results show that compared with traditional algorithms, the method proposed in this paper has improved stability and accuracy and has good practical value.

2. Wavelet Transform and Long Short-Term Memory Network Model

Wavelet analysis can be used to detect these collected data. For any signal *f (t) = L2 (R)*, the wavelet transform is:

$$WT(a,\tau)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(t)\times\psi(\frac{t-\tau}{a})dt \tag{1}$$

Among them, the average amplitude of the wavelet in the time domain is 0; the basic wavelet ψ of the wavelet has a scale α translation amount τ; the wavelet parameters can be scaled and translated to achieve the decomposition of the input time domain signal. The signal *f (t)* does not necessarily remain continuous. A discontinuity at some point or a discontinuity in a certain order will lead to singularity. During monitoring, Lipschitz index β is used to measure the degree of singularity of the power line. The maximum values of wavelet transform t0 and The abrupt point of the signal corresponds, and the existence of a constant K makes the wavelet transform have the following relationship:

$$|WT_{\max}(\alpha,t_0)|\le K\alpha^{\beta} \tag{2}$$

Where β is [0,1], when the wavelet is a binary wavelet, formula (2) can be expressed as:

$$\log_2\left|WT_{\max}(a,t_0)\right|\le\log_2 K+j\beta \tag{3}$$

For ordinary line noise β, the wavelet transform maximum value WT_{max} will decrease rapidly; conversely, when the signal is abrupt, β will make the wavelet transform maximum value WT_{max} increase or stay the same as the scale increases. Key features of data and noise.

Long Short-Term Memory (MLSTM) is a model widely used in the current deep learning field for sequence and signal processing. Due to the consideration of both the time series and non-linear relationships of data, it has been widely used in time series data prediction [6]. Using MLSTM can solve the length-dependent problem of traditional time series processing algorithms and achieve higher prediction accuracy. The structure of MLSTM is shown in the following figure:

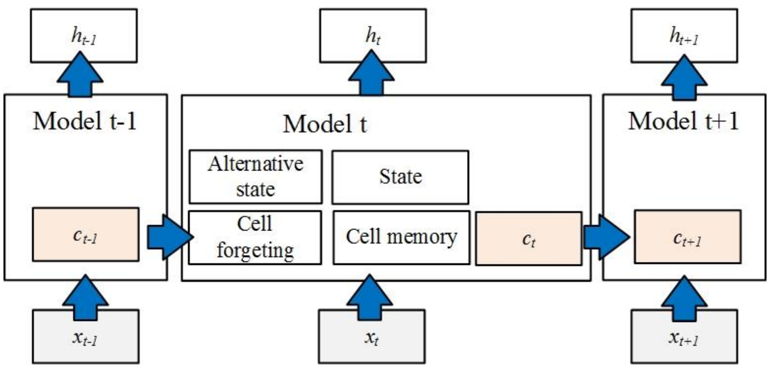

Figure 1. Structure of the MLSTM

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As shown in Figure 1, MLSTM consists of multiple models, each model corresponding to the input xt, output ht, and the state Ct transmitted to the next module, where t is the sequence number [7-10]. For a module that contains four neural network calculations, the corresponding formula for the forgotten input data is as follows:

$$f_t = sigmoid(W_f[C_{t-1}, h_{t-1}, x_t] + b_f) \tag{4}$$

W_f and b_f are the weights and biases of the forgotten part of the data. This formula can determine the degree of attenuation of the output of the previous module. The formula corresponding to the repeated part of memory is as follows:

$$i_t = sigmoid(W_i \cdot [C_{t-1}, h_{t-1}, x_t] + b_i) \tag{5}$$

Among them, Wi and bi are weights and biases corresponding to an input gate layer, and an alternative state is constructed on this basis:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$

Among $\tilde{C}_t$ is candidate states, and W_C and b_C are corresponding weights and biases. Combining formulas (1) (2) and (3), the state of the output of this module is:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{7}$$

Based on this output state, the output of the module is:

$$h_t = sigmoid(W_O[C_{t-1}, h_{t-1}, x_t] + b_o) \times \tanh(C_t) \tag{8}$$

Through this process, the memory of the previous node is transmitted to the next node, and the weight of each part is optimized by the training data to achieve the purpose of sequence data analysis. It can be seen from the formula that each module of the MLSTM contains two parts of forgetting and memory, which can realize the memory process of the input value within a certain sequence range. This feature is very important in the process of sequence data processing. For the results of wavelet transform processing, you can directly use MLSTM to solve the problem of scale parameters. Introduce the MLSTM algorithm to find the characteristics of changes between different scales of the wavelet instead of locking changes in specific scales, so as to effectively detect the data.

The section headings are in boldface capital and lowercase letters. Second level headings are typed as part of the succeeding paragraph (like the subsection heading of this paragraph). All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your paper. Please keep a second copy of your manuscript in your office. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question. When receiving the paper, we assume that the corresponding authors grant us the copyright to use.

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3. Fiber Raman Temperature Measurement Detection Algorithm Based on Multi-Scale MLSTM Integration Model

The multi-scale MLSTM integrated model proposed in this paper, the model training and construction methods are as follows:

If the construction of a multi-scale MLSTM integrated model (M-MLSTM) is shown in two stages:

The first stage: the construction of the scale sub-MLSTM, the content of different scales of the input data are grouped according to the scale, and each group corresponds to independent scale and result data. Based on this data, a separate MLSTM model is constructed to form a scale model group submodel = {sub1, sub2, ..., subn}.

The second stage: the construction of M-MLSTM, locking the weight values of all submodels in the submodel, connecting each element of the submodel as an output sequence to an MLSTM, and still using the result data as a driver to train an MLSTM model for integration, elstem . Construct an M-MLSTM model, which contains a list of submodels that perform preliminary processing on the input and elstem for integration decisions, and can finally detect fluctuations.

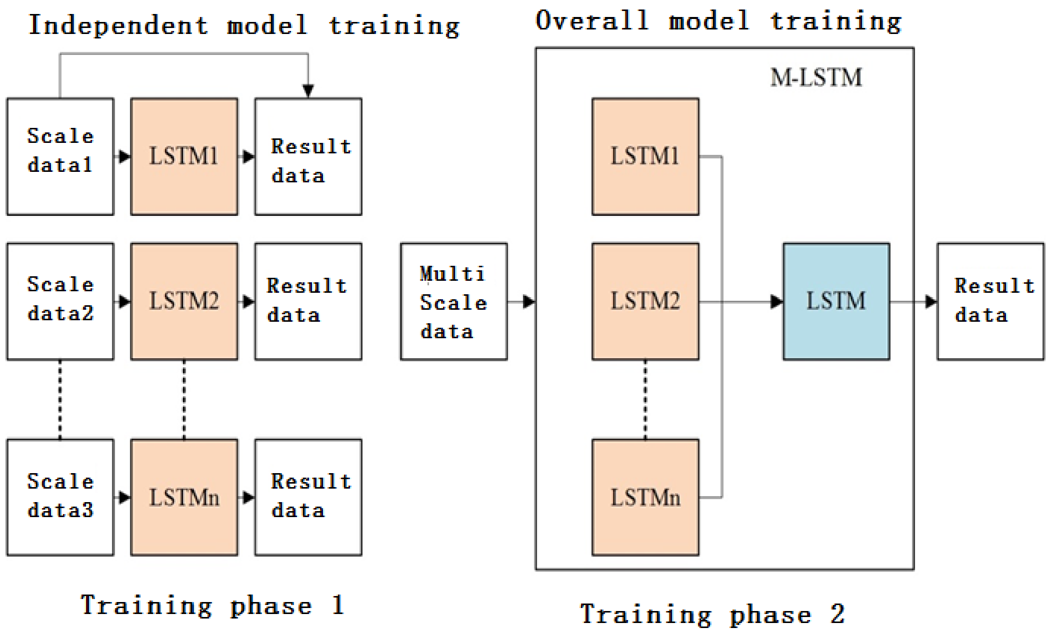

Figure 2. Training and construction of a multi-scale MLSTM integration model

The typical benefit of using the M-MLSTM model in this paper is that the model is not bound to specific scales and input data, but instead discovers deeper features of the wave in the change process, thereby achieving sensitivity to various scales. For the targets that are detected without being confused with noise, the TWH-M-MLSTM algorithm is organized as follows:

(1) Enter the information number data: Enter the information number data and mark the collected data to build a training data set.

(2) Wavelet transform: Perform wavelet transform multi-scale analysis on the input data to obtain the corresponding scale analysis results.

(3) Training model: The results of signal processing are trained according to the content described in 3.1.

(4) Obtaining a prediction model: Obtain an M-MLSTM model, which can input data and make detection results, and implement the TWH-M-MLSTM algorithm through the above process.

4. Simulation

This paper implements all algorithms through Python 3.5, constructs a simplified fiber Raman temperature measurement structure in the laboratory, and builds an experimental data set in the laboratory environment. With the above parameters, 5,000 fiber Raman temperature measurement sample data are constructed. Normal operation but contains 5,000 pieces of noise data. In order to further verify the accuracy and stability of the algorithm, 1000, 2000, and 3000 training data are selected as training data sets. The proposed method is compared with SVM, wavelet + SVM, Kalman filter + SVM, and MLSTM. The accuracy is shown in the following table:

Table 1. Accuracy comparison

Sample Size	SVM(%)	Wavelet + SVM(%)	Kalman filter + SVM(%)	MLSTM(%)	TWH-M-MLSTM (%)
1000	61.83	72.37	69.61	66.73	710
2000	61.97	69.8	69.5	69.71	73.42
3000	64.15	79.11	74.31	7286	79.19
4000	64.53	76.21	77.94	75.57	79.98
5000	73.17	78.14	79.48	78.82	83.86

As can be seen from the table above, the accuracy of processing directly using SVM is often low, and the accuracy is significantly improved after the introduction of multi-scale wavelet and Kalman filtering, but the accuracy fluctuation is more obvious when there are fewer samples. It has the ability to process sequence data, and the detection accuracy is improved compared with SVM. The TWH-M-MLSTM algorithm proposed in this paper has achieved good detection results under various sample sizes.

5. Conclusion

Fiber-optic Raman temperature measurement is difficult to obtain data efficiently and accurately due to the differences in equipment and environment, and the existence of multiple noises. In response to this problem, a multi-scale MLSTM integrated model-based optical fiber Raman temperature measurement detection algorithm is developed in this paper. Multi-model integration is used to solve the previous algorithm's problems of binding to specific scales and parameters, and low detection capability. Simulation experiments show that the proposed algorithm has advantages in accuracy and stability, and has higher practical application value.

Acknowledgements

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