Wavelet Transform and Stacked Sparse Autoencoder Network Based Location Method of Cable Incipient Fault

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Abstract. Incipient fault of power cables can easily evolve into permanent fault, which endanger the safety and stability of power systems seriously. In order to detect and solve the incipient fault of cables in time, in this paper, a fault location method based on combination of wavelet transform and stacked sparse autoencoder is proposed. Wavelet transform is used for feature extraction of fault signal, and the original signal is decomposed into time domain features of different frequency bands. Stacked Sparse Autoencoder network takes these features as input, training and forecasting, and finally determines the location of fault signal. Experiments show that the method we proposed can locate the incipient fault of power cables quickly and accurately.

Keywords: Incipient fault, wavelet transform, stacked auto encoder, location.

1. Introduction

With the reform and development of urban power grid, power cable has been widely used in urban power supply system because it is not easy to be affected by the environment and has low maintenance rate. However, power cable has complex laying environment. In case of failure, the lack of timely and accurate fault location technology will lead to power fault for a long time, which will certainly affect the normal production and life of residents and cause serious losses. Therefore, it is of great significance for the security and stability of power supply system to realize accurate positioning of incipient cable fault.

In general, incipient fault of power cables will occur repeatedly. If targeted maintenance is carried out in a timely manner after the detection of incipient fault in cables, it can be avoided to deteriorate into permanent fault [1].

At present, the research on cable fault at home and abroad mainly focuses on fault identification and location. Incipient fault of cables usually occurs at peak voltage, which is regarded as the characteristic of incipient fault [2-4]. For the moment, the used signal processing methods are time-frequency transform commonly, such as wavelet transform [5], S transform [6], etc. to extract fault signal features. Different from the Fourier transform lacking spatial local features [7], also different from the S transform which has poor resolution on high frequency part of the frequency domain. The wavelet transform has good time-frequency domain characteristics and good signal self-adaptive ability. It can describe the singularity of nonstationary signals almost perfectly [8]. Both [9] and [10] proposed to determine the location of cable fault based on wavelet transform modulus maxima. In [11], the wavelet transform is used to detect the time when the fault waveform reached the measuring end and establish a system of equations to solve the fault distance. Some fault signals are classified and identified through neural networks. For example, the paper [12] proposes to construct fault location optimization neural network model to predict the location of fault points. Both [13] and [14] have added BP neural network for disturbance recognition and location. The neural network has been used widely in various fields due to its powerful learning and judgment ability and achieved quite satisfactory results.

In this paper, wavelet transform is combined with the neural network composed of stack sparse autoencoder [15] and softmax classifier [16] to locate the incipient fault of cables, which overcomes the limitations of using various methods alone. By inputting fault feature data after wavelet transform into the neural network, so dimension reduction of high-dimensional data is realized. On the other hand, the stack sparse autoencoder completes the initialization of the weights of the whole neural network at the same time of training. The simulation results show that the proposed method can locate the incipient fault of the cable quickly and effectively.

2. Feature Extraction

2.1 Analysis of Cable Incipient Fault Signal

In this paper, the 40 incipient faults of different distances mentioned are restored by PSCAD/EMTDC simulation according to the field fault waveform. Because there are too many kinds of fault signals, only 500m, 5500m, 10500m, 15500m and 20000m fault signals are selected for display (Fig. 1).

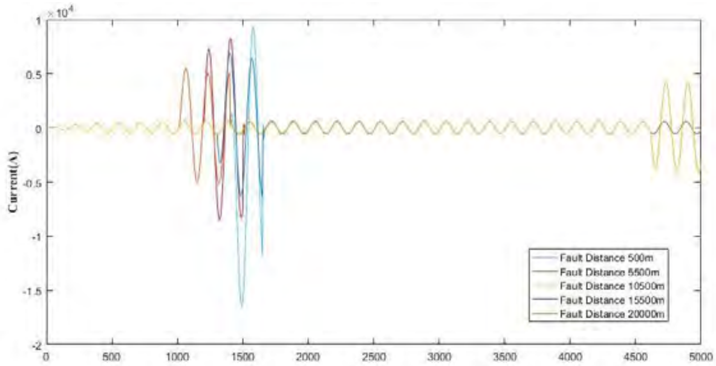

Fig. 1 Five incipient fault signals for cables of different distances

As shown in the Fig.1, the original waveforms of fault signals at different distances are very similar, but under the noise interference of the real environment, direct location recognition not only takes too much time, but also has a low accuracy. Wavelet transform has the ability to analyze nonstationary signals effectively. Due to it has good time resolution at high frequency and good frequency resolution at low frequency, so the frequency component of the signal can be obtained and the fault can be located accurately. Cable incipient fault signal belongs to nonstationary signal, so we use wavelet transform to as preprocessing.

At the same time, it is not difficult to observe the incipient fault waveforms of different distances have different amplitude and kurtosis of the waveforms. In order to improve the recognition efficiency and avoid the input redundancy of stacked sprase autoencoder, which leads to excessive computational effort. On the Basis of Wavelet Transform, We extracted 6 features, of which $w_k[n]$ is the decomposition signal of the k layer of wavelet transform, N is the total length of the signal, $1 \le n \le N$:

Mean value:
$$\mathrm{MEV} = \frac{\sum_n w_k[n]}{N} \tag{1}$$

(Estimate the DC component of the signal.)

Root mean square:
$$\mathrm{RMS} = \sqrt{\frac{1}{N}\Sigma_n w_k^2[n]} \tag{2}$$

(Measure the overall strength of the signal.)

Peak factor:
$$CF = \frac{Max(w_k[n]) - Min(w_k[n])}{RMS} \tag{3}$$

(Represents the extreme degree of signal peak value in waveform.)

Energy:
$$EN = \sum_{n=1}^{N} w_k^{\ 2}[n] \tag{4}$$

(Describe the overall energy of the signal.)

Energy entropy:

$$ENt = -\sum_{i=1}^{N} \frac{w_k{}^2[n]}{EN_k} \log_2 \left(\frac{w_k{}^2[n]}{EN_k} \right) \tag{5}$$

Where, EN_k is the energy of the k layer of wavelet transforms;

Shannon entropy:

$$p = \frac{w_k^2[n]}{\sum_n w_k^2[n]} \tag{6}$$

$$SE = -\sum_n \left(p \cdot log_2(p) \right) \tag{7}$$

(The calculation of the entropy feature indicates the uncertainty of the signal.)

The above 6 features are inputted into the neural network for analysis, and the corresponding relationship between the fault signal and the fault distance is established. Because there is a nonlinear mapping relationship between the modulus maxima of wavelet transform and the sudden change point of signal [17], it is also analyzed as a contrastive algorithm.

2.2 Principle of Wavelet Transform

As extension and development of Fourier transform, the wavelet transform method uses finite-length attenuated wavelet base to superimpose the original signal to obtain the required time-frequency characteristics.

Wavelet transform of the original signal is shown in (8):

$$WT(\alpha, \tau) = \frac{1}{\sqrt{\alpha}} \int_{-\infty}^{\infty} f(t) * \psi \left(\frac{t-\tau}{\alpha} \right) dt \tag{8}$$

Where, α is the scale of the expansion of the wavelet transform; τ represents the translation transformation of the wavelet transform. The time domain characteristics of the original signal at different frequencies can be obtained by setting the scaling and translation of the wavelet transform. Multilayer wavelet decomposition of the original signal, which is the characteristics of the signal in different frequency bands are obtained by multi-wavelet analysis.

By choosing the appropriate wavelet for wavelet transform [18], all the features in the original data can be obtained. In experiment, the fault signal is decomposed by 6 layers wavelet using Db4 wavelet.

3. The Construction of Neural Network Based on Sparse Autoencoder

Artificial neural network has made great progress in recent years. It has made remarkable achievements in many fields, such as pattern recognition, image processing, prediction and analysis. It can provide great help to solve practical problems [19]. In this paper, the sparse autoencoder can provide good initial values of weight parameters for the neural network. By stacking multiple sparse autoencoders, the neural network with multiple hidden layers is constructed. The nonlinear mapping relationship between these features and fault distance is learned by using the fault signal features extracted by wavelet transform, so as to locate the incipient fault of the cable.

3.1 The Structure of Sparse Autoencoder

Autoencoder is a symmetrical neural network model, which general includes three parts: input layer, hidden layer and output layer. Sparse autoencoder is a neural network model which adds sparse restriction to autoencoder. Its structure is shown in Fig. 2.

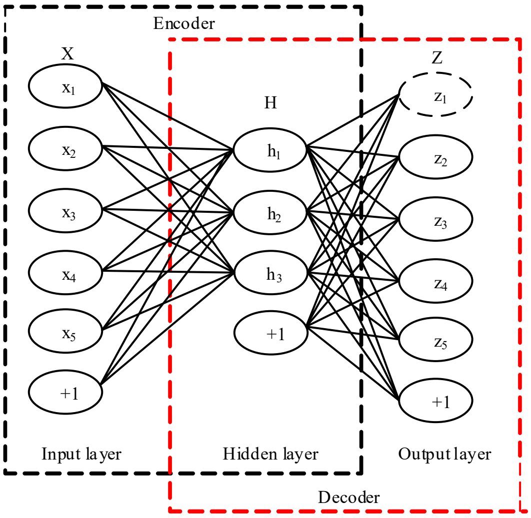

Fig. 2 The structure of sparse autoencoder

It is not difficult to show from Fig.2 that the sparse autoencoder has three layers neural network, in which the first two layers of neural network complete the coding process and the last two layers of neural network complete the decoding process, and lastly, the output approximates the input through back-propagation algorithm

On the other hand, the number of neurons in the hidden layer of sparse autoencoder is significantly less than that of the input layer, which makes the sparse autoencoder have its most important feature, that is, to obtain the best expression of the hidden layer by reconstructing the input data.

3.2 Constructing Sparse Autoencoder

In the training process of supervised neural network, our training data include both input data and given expected output. Only in this way can we construct the loss function and obtain the loss function to executive the training of the neural network model. In typical unsupervised neural networks, sparse autoencoder only have training data but no expected output. In order to complete the training of the encoder, we still need to construct loss function. In the sparse autoencoder, we assume that the expected output is the same as the input value. In this way, the process of encoding and decoding realizes the compression and reproducing of the input signal, thus obtaining the best hidden layer expression of the input data, and using the mean square error to construct its cost function as shown in (9):

$$J(W,b)=\frac{1}{2}\|Z-X\|^2 \tag{9}$$

Where, Z is the output value and X is the input value.

In this experiment, sigmoid activation function is used for sparse autoencoder. In order to restrict the sparsity of the autoencoder, the output of most hidden layer neurons is close to 0. We define the average activation of hidden neuron as shown in (10):

$$\hat{\rho}_j=\frac{1}{m}\sum_{i=1}^{m}[a_j^{(2)}(x^{(i)})] \tag{10}$$

Where, m is the number of neurons in the first layer. We hope that most of the neurons are suppressed. Therefore, we add a sparse parameter ρ which is close to zero, order $\hat{\rho}_j=\rho$. At the same time, if $\hat{\rho}_j$ and ρ have significant difference, in order to punish this case, so add penalty factor $\sum_{j=1}^{n} KL(\hat{\rho}\|\rho)$ (n is the number of hidden neurons) based on relative entropy. Its expression is shown in (11):

$$KL(\hat{\rho}_j\|\rho)=\rho log\frac{\rho}{\hat{\rho}_j}+(1-\rho)log\frac{1-\rho}{1-\hat{\rho}_j} \tag{11}$$

Equation (11) shows that the relative entropy increases with the increase of the difference between $\hat{\rho}_j$ and ρ, which is zero when $\hat{\rho}_j = p$. Then the total cost function of sparse autoencoder is obtained as shown in (12).

$$J_{sparse}(W,b) = J(W,b) + \beta \sum_{j=1}^{n} KL(\hat{\rho}_j \| \rho) \tag{12}$$

The sparse autoencoder [20] can reduce the dimension of high-dimensional original data, and achieve concise expression without losing key features, and improve the training speed and performance of the whole neural network. On the other hand, the performance of the neural network to a large extent depends on the initialization of the weights, and the sparse autoencoder can provide the initial weights for the neural network which is easy to predict, which is conducive to improving the prediction accuracy.

3.3 Stack Sparse Autoencoder

The neural network model consisting of several sparse autoencoders connected together is called stack sparse autoencoder [21]. The output of the hidden layer of the former sparse autoencoder is used as the input of the latter layer. Through the characteristics of the sparse autoencoder, it is known that each hidden layer will transform the input signal nonlinearly. Thereby, the more abstract expression of signals can be realized, more detailed features can be obtained, and the feature expression can be more compacter. The stack sparse autoencoder structure is shown in Fig. 3.

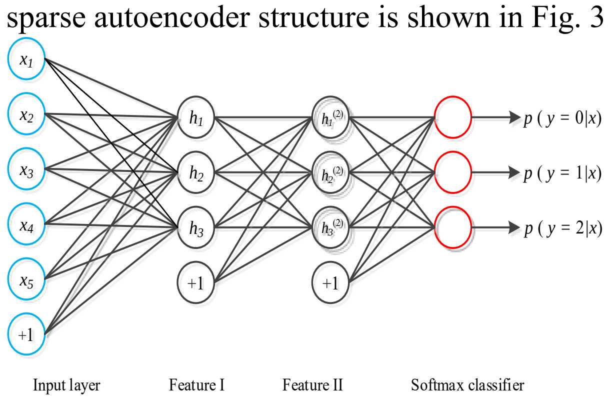

Fig. 3 The structure of stack sparse autoencoder

In Fig. 3, it can be seen clearly that the input fault feature signal is inputted into the classifier in more abstract form after being processed by two hidden layers, which improves the speed and accuracy of classification greatly. For the deep network, greedy training method is usually used to obtain the weight expression of each layer [22]. Adding stack sparse autoencoder can optimize the weight expression of the whole neural network to a great extent, and finally complete the training of the whole neural network model to achieve better results.

3.4 Softmax Classifier

Different from traditional binary classifiers such as logistic regression and SVM, softmax classifier can realize multi-classification of input features, that is, recognition of multi-class features in a classification process.

The reason why softmax classifier can achieve multi-classification is that it uses the softmax activation function, which is expressed in (13):

$$y_i = \frac{e^{a_i}}{\sum_{k=1}^{K} e^{a_k}} \tag{14}$$

Where, K is the total number of needed categories and a_1 is the input signal. Its output can be seen as belonging to all kinds of probability size.

The stack sparse autoencoder adopts unsupervised learning, but the softmax classifier is a supervised neural network. The combination of the two makes the whole neural network model not only have the strong learning ability of unsupervised network, but also have the reliability of supervised network, and can locate the incipient fault signal of cable quickly and accurately.

4. Wavelet Neural Network Location Method

In this paper, wavelet transform is used to extract the features of cable incipient fault signals and input them into stack sparse autoencoder for feature nonlinearization. Then the abstracted feature data are input into the classifier to classify and determine the location of the incipient fault. The method flow is shown in Fig. 4.

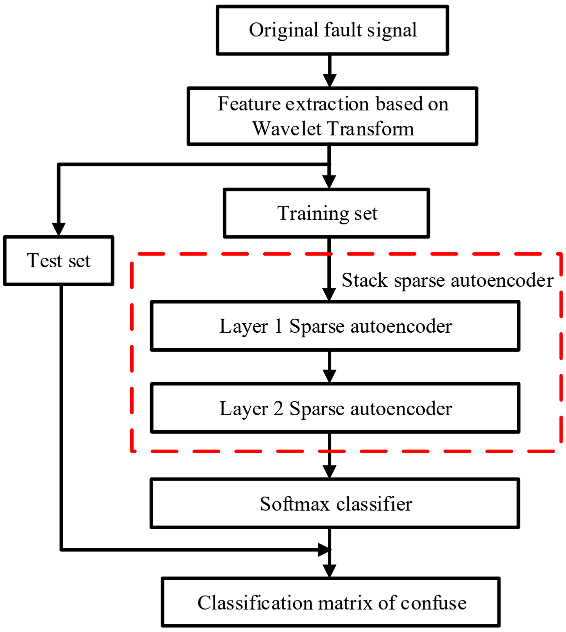

Fig. 4 Flow chart of incipient fault location method for cable based on wavelet neural network

The method is implemented in the following steps:

Firstly, the power cable simulation model[23] is constructed in PSCAD/EMTDC, and obtain the incipient fault signals at different fault locations, thus make appropriate labels for fault signals of different distances.

In MATLAB, wavelet transform is used to extract fault signal features from the obtained incipient fault data. The extracted features are divided into training set and test set.

The training set and the training target vector are input into the neural network to train the neural network model, and to get the corresponding relationship between the fault signal and the fault distance is established.

The test set and the test target vector are input into the trained neural network and output the classification results.

5. Example Analysis

5.1 Data Sets

We evaluate proposed approach using simulation fault signal data which simulation circuit model in PSCAD is shown in Fig. 5.

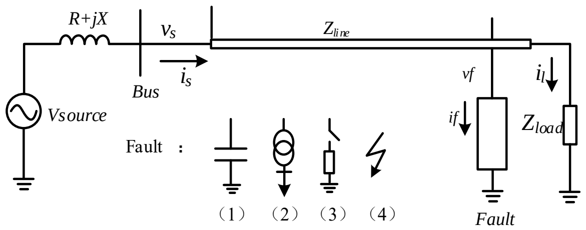

Fig. 5 Cable incipient fault signal simulation circuit model

In our experiment, the incipient fault signal in the range of 20000 meters was sampled with sampling frequency of 10 kHz. And classify the fault signal at intervals of 500 meters to obtain the data sets.

5.2 Classifier and Approaches

We take 6 layers of wavelet decomposition on the original data sets using db4 wavelet. Each layer of wavelet decomposition generates two coefficients: detail (high frequency) coefficients and approximation (low frequency) coefficients. Due to the nonlinear mapping between the wavelet transform modulus maximum point and the sudden change point of signal, we extract 6 measures to simulate fault signal location problems: the mean value, root mean square, crest factor, energy, energy entropy and shannon entropy. There are 7 layers of coefficients after wavelet transform: 6 detail coefficients and 1 approximation coefficients. We extract 6 features on each coefficient. Therefore, a total of 42 features are extracted for each signal for location analysis.

Fig. 6 is the wavelet coefficient of the partial fault signal after 6 layers decomposed by db4 wavelet transform at each frequency scale.

We use 3600 incipient fault signals as data sets in the experiment, and 2800 of them as training sets, the rest as test sets. Then extract training sets and test sets features by wavelet transform. The first sparse autoencoder sets 49 input units and 20 hidden layer units to reduce feature dimension. The weight regularization coefficient is set to 0.001. The penalty term regularization coefficient is set to 4. The sparsity parameter is 0.05. Since the second layer sparse autoencoder uses the hidden layer elements of the first layer as input, so sets 20 input units, and the other settings are same as the first sparse autoencoder. Then training the classifier with the hidden layer element of the second sparse autoencoder and the train label (trainning target vector) as input to the softmax classifier. The first two sparse autoencoders parameters are used as initialization parameter values of the entire neural network model to improve classifier performance. After training, we input test set and real label (test target vector) into neural network for classification test.

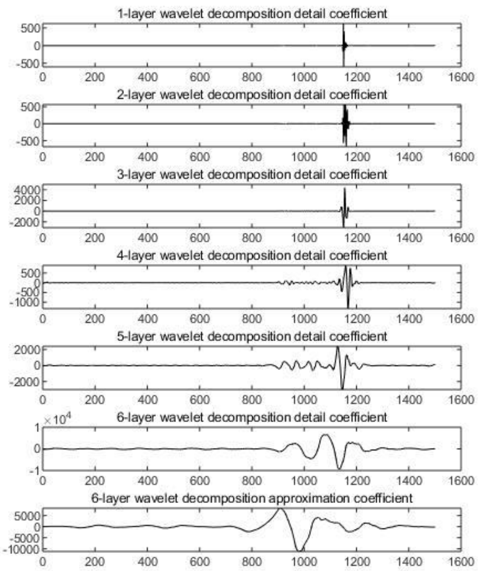

Fig. 6 Wavelet coefficients of 6 layers decomposition of db4 wavelet

5.3 Results and Discussion

We plot the confusion matrix to analyze the classification performance of the softmax classifier and the incipient fault location. The result is shown in Fig.6. (Because the 40*40 confusion matrix is not convenient to view in the paper, we plot Fig.6 based on confusion matrix.)

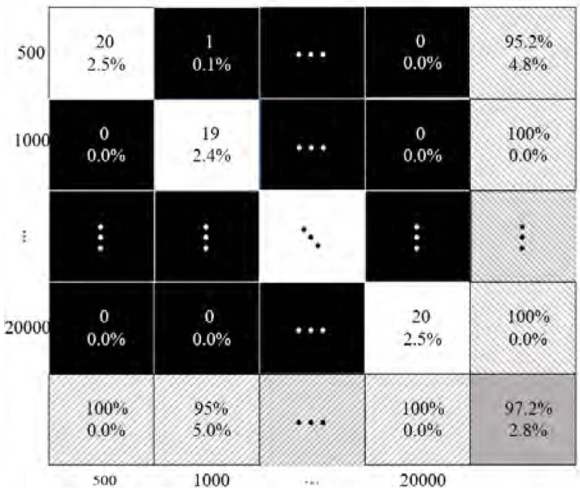

Fig. 7 The confusion matrix of fault distance

There are many performance measures for binary classification such as accuracy and area under curve. For the multi-classifiers such as softmax, it is general considered to evaluate performance with confusion matrix.

The ordinate in Fig.7 represents the classification result, and the abscissa represents the label value. The white area on the diagonal indicates the number of correct classification samples and their proportion. Other black areas indicate the number and proportion of misclassified samples. The lower right corner shows the overall classification accuracy. It is shown in Fig.7 that the accuracy of 40 classifications for test sets is 97.2%. Three samples were misclassified into other classes. The first row and the second column of data show that the incipient fault signal was misallocated to 500 meters, which should have been at 1000 meters.

5.4 Compared With Other Fault Location Methods

At present, feature extraction is often used for power cable fault location and the fault location is calculated or derived based on the extracted features. The proposed method and the wavelet transform modulus maximum method are used to locate the accuracy rate as shown in Table 1.

Table 1 Accuracy comparison of two methods

Location method	Accuracy (%)
Proposed method	97.2
wavelet transform modulus maximum method	96.9

It is shown in Table 1 that the proposed method in this paper has higher accuracy for fault location. In addition, the process of dealing data has higher reliability and faster speed. Therefore, our method more practical for processing of large amounts of data.

Compared with the location method that directly sends data into the classifier without wavelet transformation and removes the stacked sparse autoencoder, the result is shown in Table 2.

Table 2 Comparison of positioning effects of three methods

Location method	Sample number	Number of misclassified	Accuracy (%)	Time cost(s)
Proposed method	800	22	97.2	74.035
Without wavelet transformation	800	78	90.3	1240.766
Without stacked sparse autoencoder	800	44	94.5	55.214

It can be clearly seen in Table 2 that feature extraction great reduces the dimension of features and saves a lot of neural network training time. In our experiment, 3600 feature data cost 74 seconds for analyzed and location. But it takes more than 20 minutes to analyze and location without wavelet transform and stacked autoencoder using softmax classifier. Therefore, the wavelet transform for feature extraction is of great significance for classification.

In addition, the accuracy of classifier without stacked sparse autoencoder is 94.5%, and 44 data were incorrectly located. This performance is not as good as the classifier proposed in this paper. It can be seen that the stacked sparse autoencoder has great advantages in optimizing the initial weight coefficient and improve the accuracy of the final classification.

6. Conclusion

Experiments show that it is feasible and accurate to use wavelet transform to extract features of cable incipient fault signals and classify them by stack sparse autoencoder and softmax classifier. The expression of confusion matrix is intuitive and detailed, and it is easy to lock the fault area. On the other hand, this method has a certain anti-noise ability, and can still locate incipient faults accurately under the condition of extracting multiple features. It can be seen that this method has strong robustness and is not easy restricted by the environment, such as terrain, climate and other conditions, so it has universal applicability.

This paper verifies the feasibility of the combination of wavelet transform and stack sparse autoencoder in cable incipient fault location. Meanwhile, simulation data are used to study the experiment, a large number of measured data signals are needed to verify and analyze before they can be applied to practical work.

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