Using VGG Network Line Graph Semantics for Power Grid Fault Diagnostics

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Abstract: ***The first premise of building a smart grid is to achieve the stability of the power system. As the scale of the power grid continues to expand, more complex power grid structures and power grid faults have put forward higher requirements for power grid fault diagnosis. Therefore, it is very important to develop a method that can diagnose faults quickly and accurately. With the widespread application of synchronous phase measurement units (PMUs) in power grids, it is possible to accurately diagnose faulty types by analyzing high-precision data. In order to solve the problems of feature loss and slow convergence in the training process of machine learning, thispaper proposes a power grid fault diagnosis method, which converts the PMU data into a line graph as input, and realizes the power grid fault diagnosis method through the excellent neural network model VGG. First, select the appropriate electrical dimension in the PMU data and visualize it, then use VGG to learn image features, output fault diagnosis results, and finally test through the measured PMU datain a certain area. The experimental results show that, compared with the traditional fault diagnosis strategy, the method proposed in this paper can extract data features more effectively, and has the advantages of fast calculation speed, strong generalization ability, and good performance in complex situations.***

Keywords: phasor measurement unit, VGG, power grid fault diagnosis, Graph feature extraction

1. Introduction

During the operation of the power grid, it will experience internal and external uncertainties, such as weather or electrical equipment failures. At the same time, more and more new energy infrastructures are connected to the distribution network, such as photovoltaic power plants and wind power plants, which will cause the overall instability of the grid. Therefore, there is an urgent need for a method to diagnose faults quickly and accurately in the power grid.

Grid fault diagnosis is to infer electrical quantities such as current and voltage in the grid after a fault, as well as switch information such as protection and circuit breaker actions, to identify the type and nature of the fault. A good failure strategy is an important foundation for realizing the self-healing of the smart grid. Current power grid fault diagnosis strategies mainly include expert systems, artificial neural networks, analytical models, and Bayesian networks.

Wide-area monitoring systems are commonly deployed in power dispatch centers in power systems (WAMS) [1]. The wide-area monitoring system has high availability, high reliability, and high flexibility. It can enable dispatchers to monitor the dynamic process of the power grid in real time. It has become an essential part of the power dispatch automation system. It is currently widely used in the study of dynamic security analysis and control of power systems. The PMU[2] device used in the wide-area monitoring system has a high sampling frequency and good real-time performance. It can provide high-precision data for grid fault analysis, and can directly determine the type and nature of the fault through data analysis. [3] Proposed a PMU-Embedded Convolutional Neural Networks for real-time grid monitoring, realizing high-precision classification of multiple types of time in the grid, and real-time perception of the state of the grid. [4] proposed a method for solving the fault detection and isolation probability of smart grid transmission lines using PMU data. [5] proposed a PMU data-driven framework for classifying destructive events in the distribution network.

Artificial neural network [6-7] is a kind of simulating human nervous system, through learning digitized text, image, voice and other data, mining data features, find the general rules from input to output, so as to predict and predict unknown information. judge. Neural networks play a prominent role in the field of power grid fault detection and diagnosis. [8] A neural network-based adaptive dynamic programming method is used to control and fault detection of grid integrated photovoltaic systems. [9] built an AC-DC hybrid transmission line model to collect data, and used a series of techniques such as normalization, L2 regularization, and improved batch normalization to train the improved CNN. The experiment proved that the model can solve the fault of the AC and DC power grid. Diagnose the problem. [10] proposed an auxiliary fault identification strategy based on branched convolutional neural network (BR-CNN). The input is the voltage and current characteristic matrix, and the output is the fault and lightning interference, which can avoid the lightning interference by the primary protection of the power grid. It is judged as a DC fault, which improves the reliability of protection. [11] According to different types of faults in the distribution network, there are different power changes, select the fault characteristic quantities, simulate the sample library of electrical quantities when the fault occurs, and train the B-P neural network to realize the fault diagnosis of the distribution network. [12] proposed a fault identification method for flexible DC grid based on convolutional neural network. The input of the model is a two-dimensional matrix composed of positive and negative line voltages and a two-dimensional matrix composed of positive and negative line currents, which not only realizes the rapid identification of DC faulty types and regions, but also reliably distinguishes faults from lightning interference.

VGG [13] is a special kind of convolutional neural network (CNNs), VGG can be applied in many fields of power grid [14-15]. VGG uses multiple convolution kernels and a special convolution structure for data feature extraction, which has higher classification accuracy than traditional CNNs. Inputting the original data into the model and extracting features through convolution operation can effectively avoid the problems of information loss in the process of manual feature extraction. Therefore, VGG can be used to realize power grid fault diagnosis.

In order to improve the diagnosis efficiency, this paper converts the PMU data into a line graph, and learns the image features in VGG to extract the data features implied by the PMU data to form a power grid fault diagnosis model. The direct use of PMU data for training results in a large amount of computation and a slow convergence speed. Therefore, the PMU data is converted into a line graph to more clearly express the data change process, while improving the calculation speed and improving the efficiency of fault diagnosis. The method can promote the intelligent process of power grid fault diagnosis and enrich the basic theory of power grid fault diagnosis.

2. Fault Diagnosis Method Based on Image Feature Extraction

2.1 Data characteristics

PMU data has the following characteristics:

- PMU data is sampled regularly at a short time interval to show the whole failure process more clearly.
- PMU information is more diverse, not only including voltage and current, but also measuring phase, frequency, active power and other data, which is more advantageous when analyzing complex faults.
- PMU data can form direct observations of fault events, and can directly determine faulty equipment, avoiding the complicated reasoning process when using alarm information.
- The same time standard is adopted when collecting PMU data in the whole network, which is conducive to the analysis of the whole network.

PMU data collects the three-phase voltage amplitude, phase angle and frequency of the busbar, transmission line and double-ended circuit breaker, for the instantaneous and permanent faults of the equipment and the occurrence of three-phase short-circuit faults, A/B/C single-phase short-circuit faults, AB/ Data collection was carried out for BC/CA two-phase short-circuit faults and AB/BC/CA two-phase grounding short-circuit faults.

2.2 PMU data visualization

The amount of PMU data is large. If the PMU data is directly used to train the model, the calculation cost will be increased, and a large amount of irrelevant data will affect the result of fault diagnosis. Therefore, this paper converts the PMU data into a line graph for training. Instantaneous faults and permanent faults of electrical equipment are based on whether the reclosing is successful or not, and the action of reclosing will cause the voltage and current of electrical equipment to fluctuate; when a short-circuit fault occurs in the line, the current increases significantly, and when the bus fails, the bus voltage is If it is reduced, the current of the line connected to the bus is increased. Therefore, this paper selects the electrical quantity data of seven dimensions of three-phase voltage amplitude, three-phase current amplitude and zero sequence current amplitude of electrical equipment in the PMU data.

Take the measured PMU data in a 3s sampling period of a certain line in a certain area as an example, select seven dimensions of PMU data and convert them into a line graph:

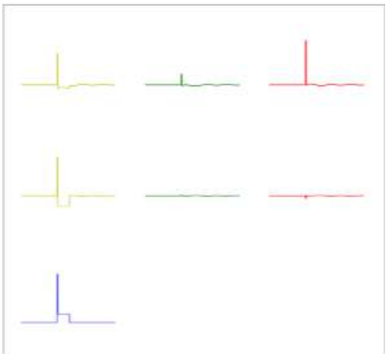

Figure 2.2-1: line graph of PMU data

The seven sub-graphs correspond to the three-phase voltage amplitude, the three-phase current amplitude and the zero sequence current amplitude of the faulty electrical equipment respectively.

2.3 VGG structure

Convolutional Neural Networks (CNNs) have become a representative in the field of computer vision. Because of their two characteristics, parameters sharing and sparsity of connections, CNNs have excellent feature extraction capabilities. In order to obtain better accuracy, there have been many variants of CNNs, and VGG is an excellent representative of them. Compared with traditional convolutional neural networks, the advantages of VGG are:

- Use a combination of consecutive small convolution kernels instead of a large convolution kernel. You can use fewer parameters to obtain better training results, and when learning image features, the relationship between the features of the target point and the features of surrounding points will be considered. At the same time, it has more nonlinearity, which enhances the generalization ability.
- Deep network layers. It can improve the learning ability, characterize more complex situations, and improve the fitting performance of the algorithm.

- More channels in the convolutional layer. Multiple channels can express richer image features, and more information can be extracted.

The structure of VGG is shown in the figure below. The model used in this article is VGG-16, which contains 16 hidden layers: 13 convolutional layers and 3 fully connected layers.

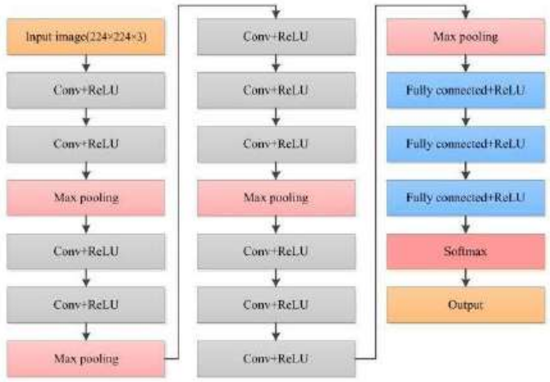

Figure 2.3-1: VGG-16 structure

The convolutional layer is used to extract the pixel-level features of the recognized image. The convolution operation is shown in the figure. The convolution kernel is a fixed-size weight matrix, which slides and covers the input matrix with a fixed step size, and is combined with the covered input sub-matrix Do calculations to obtain the output matrix. The calculation method of the convolution operation is as follows:

$$a_j^l = \sum i \in M_j^l a_{ij}^{l-1} k_{ij}^l + b_j^l \qquad (1)$$

Here, a_j^l is the j-th element value of the output matrix, a_{ij}^{l-1} is the element value of the i-th row and j-th column of the input matrix, k_{ij}^l is the weight value of the i-th row and j-th column of the convolution kernel, b_j^l is the bias, M_j^l is the input matrix set.

The pooling layer is used to eliminate redundant data and at the same time prevent the algorithm from overfitting. Similar to the sliding of the convolution operation, the commonly used pooling operation functions are max-pooling and average-pooling. The former takes the maximum value in the input sub-matrix, and the latter takes the average value of all the elements of the input sub-matrix. The pooling operation is calculated as follows:

$$c_j^l = f(c_{ij}^{l-1}), i \in N^l \qquad (2)$$

Here, c_j^l is the j-th element value of the output matrix, c_{ij}^{l-1} is the element value of the i-th row and j-th column of the input matrix, $f(\cdot)$ is the pooling operation calculation function, and max-pooling is used in this paper.

The fully connected layer means that there is a connection relationship between any two neurons between the input layer and the output layer. It is used to map the learned distributed feature representation to the sample label space to reduce the impact of feature location on the classification result. The calculation formula of the fully connected layer is as follows:

$$o = f(\sum k_i e_i + b) \qquad (3)$$

Here, is the output value, $k = [k_1, k_2, L, k_i, L, k_n]$ is the weight of the fully connected layer, $e = [e_1, e_2, L, e_i, L, e_n]$ is the n-dimensional input vector, bis the bias.

3. Power grid fault diagnosis model based on PMU data plots

This paper applies the VGG network to the diagnosis of power grid faulty types based on PMU data images, and builds a power grid intelligent diagnosis model. The input of the model is a seven-dimensional line graph drawn by PMU data.

This paper designs a classification model for two types of faults:

- Instantaneous failure, permanent failure
- AB/BC/CA two-phase short circuit, A/B/C single-phase ground short circuit, AB/BC/CA two-phase ground short circuit and ABC three-phase short circuit

Therefore, the faulty type classification model proposed in this paper can distinguish 20 types of faults. The structure diagram of the fault classification model is as follows:

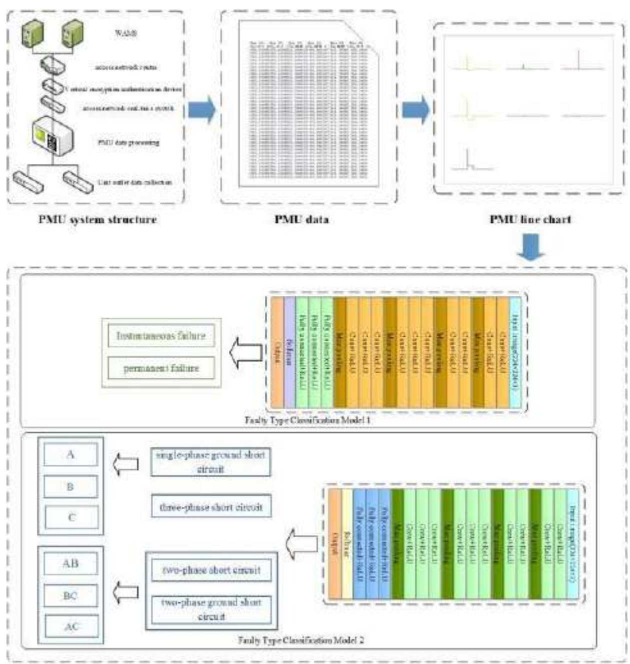

Figure 3-1: fault classification model

4. Example Analysis

4.1 Experimental data

DIgSILENT is a computer-aided engineering tool used to analyze power system transmission and distribution. This paper builds a power grid simulation model in DIgSILENT, and uses Python to automatically collect and store PMU data corresponding to various faults. The experimental data includes the PMU data output by DIgSILENT and the measured PMU data of the power grid in a certain area. After the data is converted into a line graph, it is randomly divided into training set, validation set and test set at a ratio of 8:1:1. The sample sizes of the two fault classification models are as follows:

Table 4.1-1: fault classification model 1

Failure type	Instantaneous failure	permanent failure
Sample size	1800	1800

Table 4.1-2: fault classification model 2

Faulty type		Sample size
three-phase short circuit	ABC	900
two-phase short circuit	AB	300
	BC	300
	CA	300
single-phase ground short circuit	A	300
	B	300
	C	300
two-phase ground short circuit	AB	300
	BC	300
	CA	300

4.2 Model evaluation indicators

In order to verify the classification effect of the event recognition model, the experiment uses accuracy, precision, recall and F1 value as the evaluation index of event recognition accuracy. The two-class confusion matrix is shown in Table IV.

Table 4.2-1: confusion matrix

Forecast Category	True Category	
	Positive	Negative
Positive	TP	FP
Negative	FN	TN

In the table, TP (True Positive), FN (False Negative), FP (False Positive) and TN (True Negative), In the grid fault diagnosis, Construct four evaluation indicators accuracy rate A_{cc} and F_1 value to measure the recognition effect of the model, and their expression is:

$$A_{cc} = \frac{TP+TN}{TP+FN+FP+TN} \tag{4}$$

$$P_{re} = \frac{TP}{TP+FP} \tag{5}$$

$$R_{ec} = \frac{TP}{TP+FN} \tag{6}$$

$$F_1 = \left(\frac{P_{re}^{-1}+R_{ec}^{-1}}{2}\right)^{-1} = 2\cdot\frac{P_{re}\cdot R_{ec}}{P_{re}+R_{ec}} \tag{7}$$

4.3 Parameter settings

Model training uses mini-batch stochastic gradient descent for optimization, and momentum = 0.9. Use weight decay for regularization during training. In the first two layers of the fully connected layer, dropout is used, with a coefficient of 0.5.

The learning rate is initialized to 0.01. During training, it decays a total of 3 times, and finally at 370K iterations (74 epoch), the training is stopped.

Table 4.3-1: confusion matrix parameter settings

Learning rate	0.001
Drop rate	0.5
Training size of each batch	16
The number of iterations	10
Activation function	softmax

4.4 Analysis of the experimental results

The two classification models were trained separately and tested using the test set respectively. The results show that the model can accurately diagnose the faulty types of electrical equipment.

Table 4.4-1: experimental results of model 1

Failure type	Acc (%)	F_1
Instantaneous failure	95.36	0.96
permanent failure	94.83	0.95

Table 4.4-2: experimental results of model 2

Failure type		Acc (%)	F_1
Three-Phase Short Circuit	ABC	100	1
Two-Phase Short Circuit	AB	99	0.99
	BC	99.8	0.99
	CA	99.7	0.99
Single-Phase Ground Short Circuit	A	100	1
	B	100	1
	C	100	1
Two-Phase Ground Short Circuit	AB	98.95	0.99
	BC	99.7	0.99
	CA	99.7	0.99

5. Conclusion

This paper proposes a power grid fault diagnosis model based on PMU data line graph. First, in view of the shortcomings of direct use of PMU data for training, such as large calculation amount and slow convergence speed, the PMU data is converted into a line chart that clearly reflects the fault process; then the line chart is input into two fault diagnosis models for training. The results show that the use of line chart training can have good results.

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