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Low voltage AC series arc fault detection method based on parallel deep convolutional neural network

Qiongfang Yu[1,2], Gaolu Huang[1,*] and Yi Yang[1]

[1]School of Electrical Engineering and Automation , Henan Polytechnic University, Jiaozuo Henan, China;
[2]Postdoctoral Programme of Beijing Research Institute, Dalian University of Technology, Beijing, China

*Corresponding author e-mail: huanggaolu2018@sina.com

Abstract. The complexity and concealment of series arc fault threaten the safety of household power supply system. Detection of series arc faults using threshold and characteristics extracted from current or voltage may affected by load type and connection mode. Based on AlexNet, a new parallel deep convolutional neural network detection method is proposed in this paper. The series arc fault and normal operation current signal data of three types of load totally 7200 sets were collected respectively. Using the collected data, a training data set and four test data sets were constructed to train and test the proposed convolutional neural network. The experimental results show that the detection accuracy of parallel AlexNet is higher than that of AlexNet, with a maximum of 16.75 percentage points. The stability of parallel AlexNet is about twice as high as that of AlexNet, and the maximum is close to four times.

1. Introduction

Electric plays an important role in human's life. All kinds of equipments are used and the load in power system is gradually rising. Electric safety problem is arising, which is one of the main causes of fire. According to Fire and Rescue Department of the Ministry of Emergency Management of the People's Republic of China website, from 2012 to 2016, about 30% of the fires were caused by electric safety problems[1]. Arc temperature can reach $5000°C \sim 15000°C$[2], which can ignite materials around the arc and pose a great threat to the electrical system. There are two kinds of arc in household power system[3]. One is arc fault that threat the safety of household power system, another is normal arc which is safe. This paper investigates the detection method of series arc fault, which is difficult to detect because it is affected by loads, its current usually in $5 \sim 30A$[4], almost the same with normal operation.

Some experts and scholars have done some investigations on series arc fault detection, and have made some achievements. Series arc fault can be detected by mathematical model[5] or physical phenomenon such as electromagnetic radiation[6]. Analyzing characteristics extracted from current or voltage is a primary detection method. Series arc fault can be detected by wavelet transform (WT)[7], back propagation neural network optimized by particle swarm optimization (PSO)[8] and support vector machine (SVM)[9]. It can also be detected using genetic algorithm (GA) optimized support vector machine (SVM) to identify features extracted by improved singular value decomposition[10]. In reference [11] arc fault is detected using least squares-support vector machine (LS-SVM) to identify

current feature vectors constructed by empirical mode decomposition (EMD). Time-frequency characteristics such as feature of current in mathematical morphology[12] or time domain[13,14] and high-resolution low-frequency spectral analysis[15] can also used to detect series arc fault.

However, it is hard to detect series arc fault using the characteristics when arc fault occurs, because different loads have different feature bands. The mathematical model method needs to continue to find the law of time constant and energy loss varying with other parameters. In order to avoid false alarm, the installation position of sensors must be considered when applying electromagnetic radiation method in household power supply and distribution system.

Aiming to preserve and utilize more data features and overcome randomness, concealment and complexity of series arc fault, a method with strong data feature extraction ability is needed. Deep learning is a new data processing method with powerful data feature extraction ability. By simulating the learning mechanism of human brain, the hidden features are extracted from the low level to the high level, and finally the classification is completed. It is widely used in image processing[16], pedestrian detection[17] and has achieved good results in mechanical fault diagnosis[18] and speech processing[19].

A low voltage series arc fault detection method based on parallel AlexNet deep learning network is proposed in this paper. Compared with traditional method, current signals under normal operation and series arc fault condition are directly detected, regardless of the change of current characteristics when series arc fault occurs. And the threshold is not necessary to be considered. AlexNet can extract characteristics hidden in the current signal data, and the series arc fault can be detected.

2. Principle and application of AlexNet convolution neural network

2.1. Main framework of AlexNet convolutional neural network

AlexNet is a kind of deep convolutional neural network (CNN). Unlike traditional artificial neural network that every neuron in every layer is connected with all neurons in next layer, CNN has two main characteristics of local receptive field and weight sharing. In CNN, neurons perform convolution calculation in the area covered by convolution kernel according to set strides. Therefore, one convolution kernel is used to compute all the neurons in one layer. Due to the two characteristics, the amount of parameter and computation are reduced.

AlexNet is proposed in *ImageNet Classification with Deep Convolutional Neural Networks* by Alex in 2012[20]. As shown in figure 1, it mainly contains 5 convolution layers, 3 max pooling layers and 3 full connected layers.
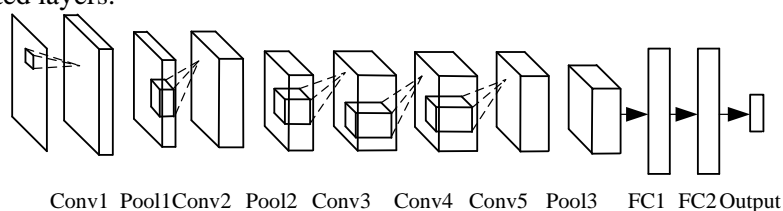

Conv1 Pool1 Conv2 Pool2 Conv3 Conv4 Conv5 Pool3   FC1 FC2 Output

Figure1. AlexNet network schematic

The purpose of convolution layer is extract data features. Convolution compute between data which are in the area covered by convolution kernel and weights, the elements of convolution kernel, is done in convolution layer, and the bias is added. Every convolution kernel has a bias. The result is mapped by activation function. After every convolution, the convolution kernel moves some strides. The strides are set manually. Convolution expression is:

$$y_{kl}^{conv} = f(x_{kl}^{conv} * w_{kl} + b_k) \tag{1}$$

where f is activation function, x_{kl}^{conv} expresses the input data covered by w_{kl}, w_{kl} expresses the convolution kernel k moves strides l, b_k is the bias corresponding with w_{kl}, y_{kl}^{conv} is output.

Max pooling layer is shown in figure 2, using a filter to extract the maximum of the area covered by the filter, and the maximum is used to represent the covered area. The amount of data can be reduced by max pooling layer.
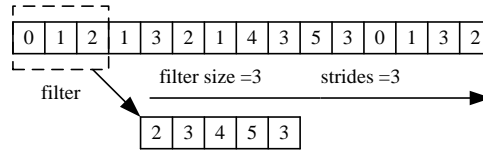
Figure2. Maximum Pooling Layer Schematic

Full connected layers play the role of classifier. The characteristics of input data are extracted by convolution layers and max pooling layers and presented as feature vectors. All these feature vectors are converted to one vector from end to end firstly and input into the classifier. Finally, the classifier outputs the classification results according to the input vector. The expression is shown as:

$$y_{j'}^{fout} = f\left(\sum x_j^{fin} \times w_j^f + b_{j'}^f\right) \tag{2}$$

where x_j^{fin} expresses the input data, w_j^f and $b_{j'}^f$ express the weight and bias corresponding with x_j^{fin} respectively, $y_{j'}^{fout}$ is output.

2.2. Activation Function

Activation function used in this paper is ReLU. The expression is shown as:

$$y = \begin{cases} x & if\ x > 0 \\ 0 & if\ x \leq 0 \end{cases} \tag{3}$$

Diagram is shown in figure 3. The output of ReLU in negative interval is 0, and it in positive interval is equal to input. Therefore, the gradient is 1 in the positive interval and 0 in the negative interval. The expression is shown as:

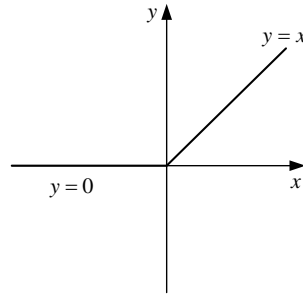$$y' = \begin{cases} 1 & if\ x > 0 \\ 0 & if\ x \leq 0 \end{cases} \tag{4}$$

Figure3. ReLU activation function

2.3. Loss Function

Loss function is an important index to judge the degree of trained network. The lower the loss function, the better the network. It can be calculated as:

a. Compute the softmax of the last layer, which represents the probability that the sample may belongs to each class. The expression is:

$$y_i = soft\max(x_i) = \frac{\exp(x_i)}{\sum \exp(x_j)} \tag{5}$$

b. Compute the cross entropy between the output vector of softmax and the actual label of the sample:

$$H_{y'}(y) = -\sum y_i' \log(y_i) \tag{6}$$

where y_i' represents the value i of the actual label, y_i represents the parameter i of the output vector of softmax.

c. Loss function can be obtained by computing the average of $H_y(y)$.

2.4. Accuracy calculation

Accuracy rate is another index used to judge the degree of trained network. The network regard the class which the maximum of the vector computed by softmax as the class that the sample belongs to then compare with the actual label of sample. Accuracy can be obtained by counting the amount of correct sample classification and calculating the proportion of it to all samples.

2.5. Parallel AlexNet

Due to AlexNet was originally used to identify picture, some adjustments and improvement are needed. Convolution function used for two dimensions should be replaced by that of one dimension, the size of convolution kernel and the pattern it slides over the input data should be changed, too. In order to obtain better result, a parallel AlexNet is used to train and test the current signal data. In the parallel AlexNet network, characteristics of every sample are extracted respectively in two branches at the same time. Finally, the two feature vectors got from the two branches added together to fuse the characteristics obtained from different feature extracting framework before input into the classifier. Diagram is shown in figure 4.
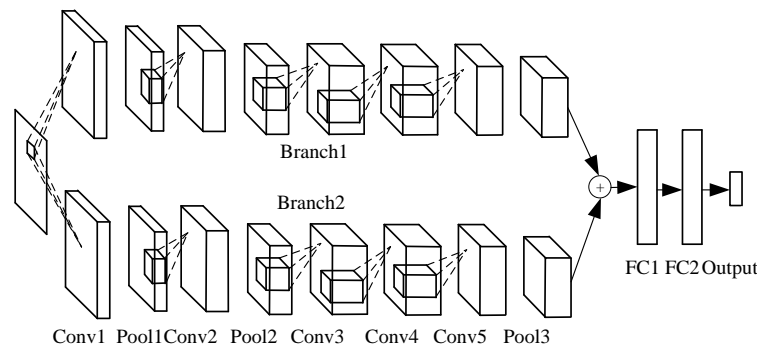

Figure4. Parallel AlexNet network schematic

3. Series arc fault experiment

3.1. Series Arc Fault Experiment Platform

Series arc fault experiment platform was built according to *Electrical Fire Monitoring System 一Part 4: Arcing Fault Detectors*[21]. There are two electrodes in series arc fault simulation generator, one is stationary made of graphite another is moving made of copper. One end of the moving electrode which is connected with stationary is burnished to be cusp. Both of them are all 6mm in diameter. Arc simulation generator is shown in figure 5. At the beginning of experiment, the electrodes are contacted in good form, then the moving electrode was moved slowly. Gap between electrodes would be breakdown by voltage and arc fault occurs. As the arc occurs, there are bright light and smoke produced by the burning of electrodes, the hissing of the arc can be heard, shown in figure 6.

The experiment circuit is shown in figure 7. In order to avoid interfere produced by normal arc or spark which are caused by switching action or bolt plug, a switch paralleling with the arc generator device is used to simulate normal arc or spark. The switch is off when arc fault current signal data are sampled. When sampling normal current signal data, the electrodes disconnect with each other. Use switch to obtain current signal data which contain interfere. A cement resistor is used for sampling. Its specifications are 100W, 1P. The platform is shown in figure 8.
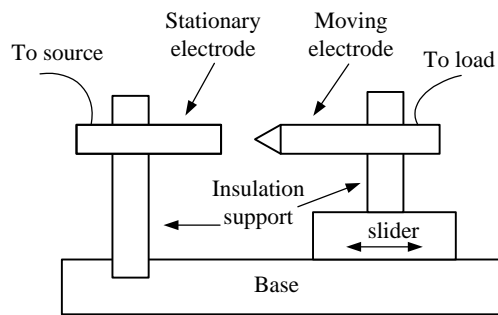
Figure5. Arc generator device schematic
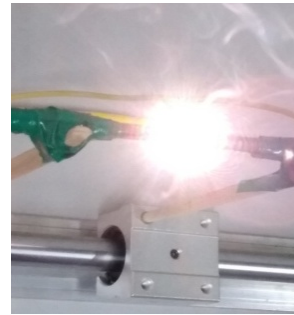
Figure6. Experimental Phenomenon
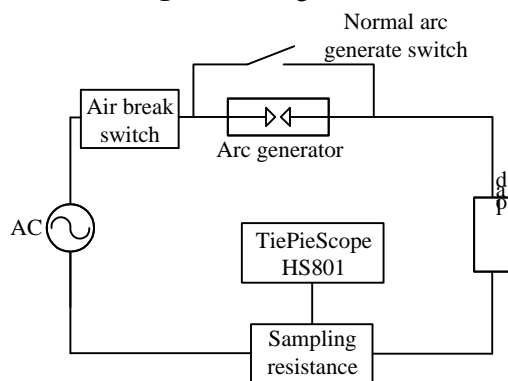
Figure7. Arc fault experiment circuit
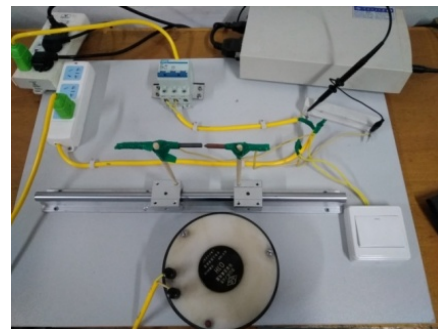
Figure8. Experiment platform

3.2. Experiment data sampling

A 200W incandescent lamp is used as resistive experiment load, a 0.1H inductance coil is used as inductive load and the series connection of incandescent lamp and inductance coil is used as resistor-inductance load. The normal operation and series arc fault current signal data of the three types of load are sampled respectively. Current signal data are sampled by TiePieScope HS801, which can automatic sample and save signal data to computer. The sampling frequency is 50kHz and there are 10 current periods in every set of data and 10000 sampling points totally. If the number of arc fault half cycles in one set of data is more than 8, it would be regarded as arc fault data.

Totally 7200 sets of data are sampled, which contain three types of load in two operation conditions. Every load in each operation condition has 1200 sets of data, 1000 sets of which are chosen randomly as training data and the rest 200 sets are used as testing data. All the training data are mixed together and arranged randomly. There are four test data sets, including three single data sets made by testing current data of every type of load in two operation conditions respectively and one mixed test data set made by all testing data. Data of every test data set are arranged randomly. Single testing data set is used to test the detection ability of trained network for every type of load and the mixed test data set is used to test the detection effect for the condition that the load type is not sure.

Current waveform of three types of load in normal and arc conditions are different obviously. Current waveforms are shown in figure 9. The normal current waveform is sinusoidal wave. The waveform with induction load is smoother than none. There is a peak at the beginning of inductance coil and incandescent lamp normal series connection load waveform, which is produced by normal arc generation switch. It does not threaten the safety of low voltage power supply system. At the end of induction coil normal waveform, the disappearing of waveform is led by the breaking of normal arc generation switch. Massive burrs or peaks exist in arc fault waveform, which are produced by high frequency parts included in arc fault. The more obvious the arc fault phenomenon, the more spikes and burrs in the waveform. At the beginning of induction coil arc fault waveform, the disappearing of waveform is led by the distance which is too far to producing arc fault. Because of the impeding effect of inductance coil on alternating current (AC), there is no peak when the circuit is connected.
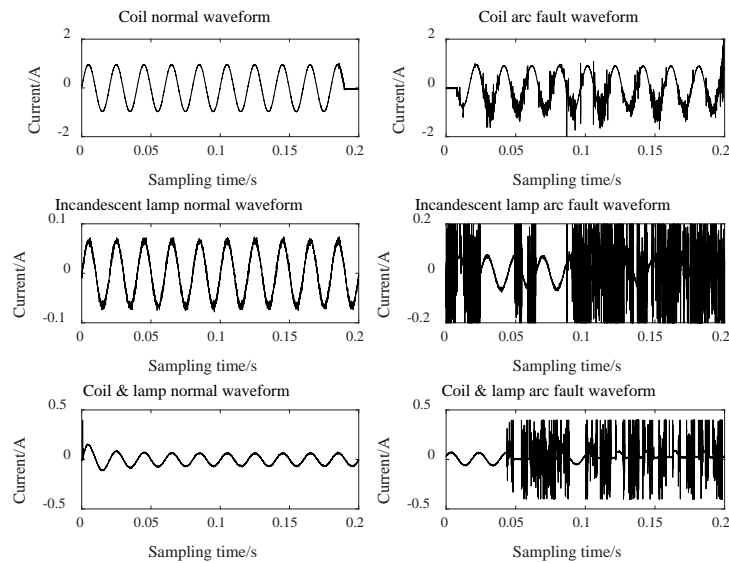
Figure9. Current waveforms

4. Experimental analysis

To present the change of training accuracy and loss function intuitively, the two curves are plotted. Figure 10 describes accuracy curves. It can be seen that both the curves of AlexNet and parallel AlexNet are convergent. However, the curve of AlexNet is more volatile than parallel AlexNet. In the first training epoch, both of them tend to convergent. Parallel AlexNet is convergent at the beginning of the second training epoch, but the similar convergent effectiveness of AlexNet is achieved in half of the third training epoch. In one word, the convergence of parallel AlexNet is faster and steadier than AlexNet.
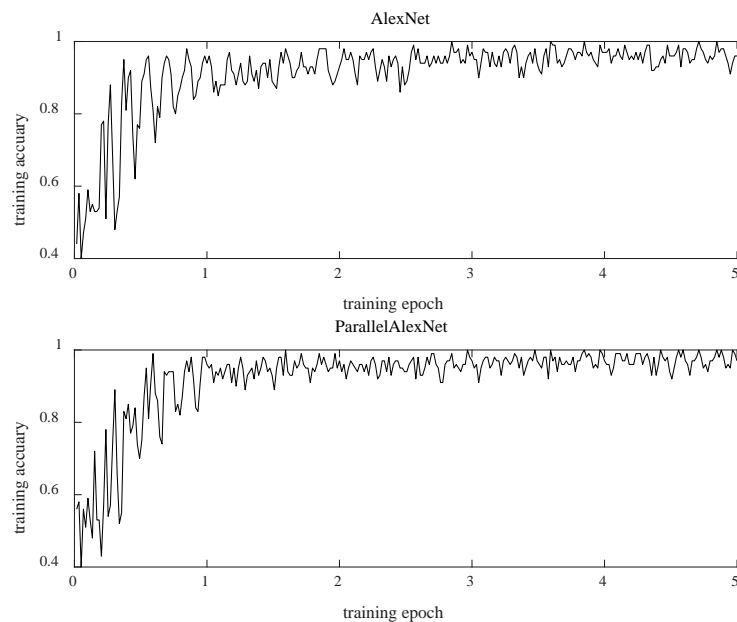

Figure10. Training accuracy curves of AlexNet and parallel AlexNet

Another index to judge the effectiveness of the trained convolutional neural network is loss function. Figure 11 is the loss function curves of the two trained AlexNet. Both the loss function of AlexNet and parallel AlexNet are convergent. Although the loss function of parallel AlexNet is larger than AlexNet at the beginning, it also reduce loss quickly in the first training epoch as AlexNet does and it converges to a lower level than AlexNet. And the undulate of parallel AlexNet is smaller than AlexNet.

Both the two indexes show that the detection ability of parallel AlexNet is higher than AlexNet, it can achieve faster and steadier detection of series arc fault.
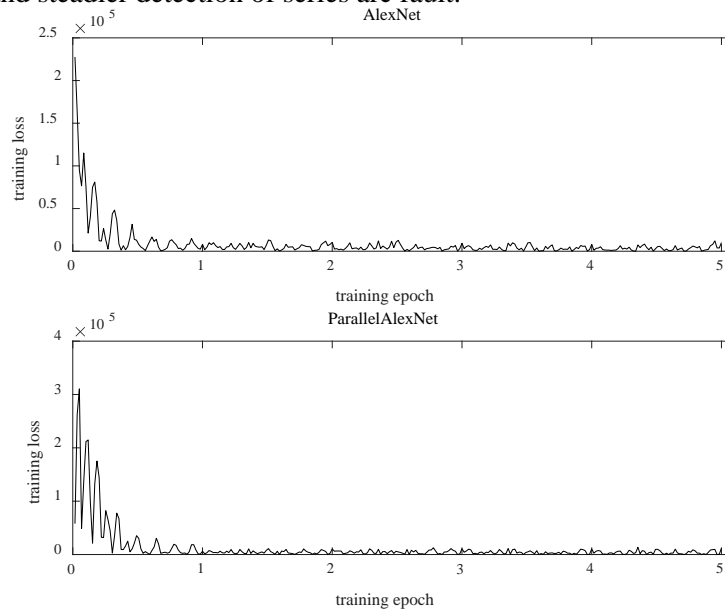

Figure11. Loss function curves of AlexNet and parallel AlexNet

The structures and parameters of the two kinds of trained AlexNets are preserved and the detection effectiveness of which are tested by testing data sets. The test results for mixed data set are shown in table 1. The accuracy of parallel AlexNet is 92%, 8.83 percentage points higher than that of AlexNet, and accuracy for every test batch is higher than AlexNet. The variance of parallel AlexNet is 0.0010, which is the 55.56% of AlexNet.

Table1. Two structures of AlexNet for three types of load mixed test accuracy table

Statistic type	Test batch	AlexNet	Parallel AlexNet
	1	88	95
	2	86	93
	3	80	89
	4	74	86
	5	86	91
Accuracy/%	6	83	89
	7	88	94
	8	79	92
	9	87	90
	10	85	97
	11	81	94
	12	81	94
	Average	83.17	92
Variance	-	0.0018	0.0010

Detection effectiveness for every type of load is shown in table 2. It can be concluded that AlexNet does best for the detection of series connection of induction coil and Incandescent lamp, which the accuracy is 88.75%, the lowest accuracy is the detection of Incandescent lamp, which is 78.25%. However, the variance for the detection of incandescent lamp is lowest, which is 0.0005. This means that the detection of incandescent lamp is the steadiest.

Parallel AlexNet does better than AlexNet for the three types of experimental load. For induction coil, the accuracy of parallel AlexNet is 84% which is slightly higher than AlexNet and the variance is only half of AlexNet. The accuracy for incandescent lamp is 95%, which is 16.75 percentage points

higher than AlexNet, and the corresponding variance is 0.0003, the 60% of AlexNet. The accuracy for the series connection of induction coil and incandescent lamp is 97%, 8.25 percentage points higher than that of AlexNet, and the variance is 0.001, less than that 1/3 of AlexNet. The difference of detection accuracy between different types of load of a kind of structure is caused by the difference of load types.

Table2. Testing accuracy of three types of load in two AlexNet structures respectively

Experimental load	Statistic type	Test batch	AlexNet	Parallel AlexNet
Induction coil	Accuracy /%	1	83	84
		2	85	86
		3	83	84
		4	79	82
		Average	82.5	84
	Variance	-	0.0006	0.0003
Incandescent lamp	Accuracy /%	1	79	97
		2	77	94
		3	81	96
		4	76	93
		Average	78.25	95
	Variance	-	0.0005	0.0003
Induction coil & Incandescent lamp	Accuracy /%	1	89	96
		2	80	93
		3	94	100
		4	92	99
		Average	88.75	97
	Variance	-	0.0038	0.001

Table 1 and table 2 show that the parallel AlexNet is not only superior to the AlexNet in accuracy, but also steadier than AlexNet.

5. Conclusion
In order to overcome the difficulties in detection produced by the characteristics of concealment, randomness and complexity, and make full use of characteristics of series arc fault, a parallel AlexNet is proposed. The series arc fault was simulated by experiment, and the data of series arc fault and normal operation (including normal arc simulated by switching action) were collected respectively. The parallel AlexNet structure was trained and tested by the collected current data. Compared with AlexNet, the parallel AlexNet structure can achieve higher accuracy and lower variance. This means that parallel AlexNet has stronger and steadier detection capability for series arc fault than AlexNet. Compared with the traditional method, it is not affected by the difference of fault characteristics caused by different load types, which provides a reference for the development of series arc fault detection device and intelligent detection algorithm.

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