

Research Article

A Fault Diagnosis Method of High Voltage Circuit Breaker Based on Moving Contact Motion Trajectory and ELM

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In order to avoid the deficiencies of conventional high voltage circuit breaker mechanical properties detection methods, a new algorithm based on image block matching with diamond search strategy is presented in this paper. The motion of auxiliary mark on the pull rod or shaft is firstly recorded by a high-speed and high-definition digital camera when the circuit breaker is open or close. Then the motion trajectory is acquired through diamond image block matching method. The mechanical parameters, such as travel and open and close velocity, are calculated according to the travel-time curve of the circuit breaker. Finally, evaluation model is constructed taking mechanical parameters characteristic values as inputs of ELM. Comparing to the existing techniques, our method is a noncontact measurement based on computer vision. It is easy and convenient for practical application since it need not any electrical and mechanical connection to the breaker. Another advantage of our method is that it can obtain the line and angle displacement simultaneously. The experiment results on the circuit breaker of 220 kv show that our method is effective for breaker mechanical properties detection.

1. Introduction

High voltage circuit breaker (HVCB) is very important in power grid operation and control. A HVCB is a device designed to open or close an electric circuit. It should be able to open circuits that operate on a wide range of capacities, varying from capacitive currents of a few hundred amperes to inductive currents of many kA. This is the main reason why it is crucial for any electric power system to ensure a reliable performance of its breakers. Statistical analysis of worldwide investigation on the reliability of high voltage circuit breakers shows that most failures of high voltage circuit breaker (70% of major faults and 86% of the minor faults) occur on mechanical system [1]. Travel-time is an important parameter to characterize properties of high voltage circuit breaker actuator performance which can directly reflect the operating state of the circuit breaker. By monitoring the circuit breaker travel-time characteristics we can obtain breaker moving contact stroke, operation time, open and close speed, and other mechanical parameters [2, 3]. Moving contact of HVCB is inside vacuum interrupter

chamber; it is inconvenient to measure the motion of moving contact directly. At present, the commonly used measurement of mechanical properties of HVCB sensor such as linear displacement transducer, grating sensors, conductive plastic potentiometers, and angular displacement sensor is that they are mounted on the circuit breaker and the movable contact is connected with synchronized movement of the insulating rod or spindle, which can measure linear or angular displacement characteristics of circuit breakers [4–7]. However, with the development of miniaturization switching devices, the shape and size of many vacuum circuit breakers have been reduced to the limit, which makes it more and more difficult to install the displacement sensors in the moving contact attachments. In addition, size of different type circuit breaker varies, the sensor clamp is not the same, which makes the installation process very complicated, and the efficiency is very low. Furthermore, low resolution and installation gaps will also affect the accuracy of the measurement. Huang et al. [8] carried out a very useful work in this area. They used high-speed video method to detect the mechanical characteristics of circuit breakers and get characteristic curve of travel and

speed by measuring mechanical characteristics of ZW17 type circuit breakers.

In the paper, based on “contactless” sensing technology and taking advantage of high-speed, high-resolution camera motion to seize image of operation driving part in the operation of HVCB, we proposed a method of image analysis and trajectory tracking technology to obtain the variable components, according to travel-time curve of circuit breaker to calculate the moving contact observation travel, (open) close time and velocity, and so forth. We use image block matching algorithm based on the diamond search to track and analyze motion of circuit breaker connecting parts, which can get linear motion and angular displacement characteristics.

In practical application, we need a reliable tool to predict when maintenance is necessary for a HVCB, avoiding undesired electric system faults. This problem can be considered as a classification task since given some input variables the system should decide on two possible outputs: “normal” or “fault.” Currently, the most popular methods in fault diagnosis are expert system and neural network. Expert system makes use of expert knowledge and experience to realize fault diagnosis. However, expert system depends on the expert knowledge acquisition, which is recognized as the bottleneck problem in research and development. In addition, expert system has various limitations, such as adaptive capacity, learning ability, and real-time performance. Neural network is an effective method to solve complex nonlinear problem, but it has some shortcomings, such as slow convergence, local minimum points, overlearning and underlearning.

State-of-the-art fault diagnosis methods include time series method, backpropagation neural network (BPNN), and support vector machine (SVM). The time series method is simple and intuitive, but it is not ideal for diagnosis of nonlinear system [9]. BPNN has the ability of independent learning and nonlinear fitting, but it has shortcomings such as slow convergence speed and long training time and local optimum [10–12]. SVM has good generalization and nonlinear fitting ability while avoiding the shortcoming such as local optimum, dimension disaster, and small sample, but it has complex calculation and it is difficult to determine the regularization parameter and kernel function parameter which will affect model performance [13–15]. Extreme Learning Machine (ELM) [16] is a useful learning model for training single hidden layer feedforward networks (SLFNs). In ELM, node parameters of input layer, hidden layer, and hidden layer weights deviation are generated randomly and then fixed without iterative tuning, and output layer weight is obtained by calculation. In training process, we can obtain the unique global optimal solution by setting neurons number of hidden layer without adjusting network parameters. In this way, ELM can overcome problems of traditional neural network, such as long training time and overfitting. Compared to popular machine learning methods, ELM has the merits of easy structure and strong learning and generalization ability. ELM has been widely used in various machine learning tasks, such as pattern recognition and regression estimation [17–20]. Compared with SVM, ELM is better in parameter optimization and convergence speed with

similar classification performance. ELM has been widely used in pattern classification, prediction, and so on.

The failure type and reason of HVCB are various, while actions of HVCB are infrequent, so we should choose fault classification method with small sample. To avoid limitations that regularization coefficient and kernel function must satisfy inherent Mercer condition of SVM, we use the Extreme Learning Machine (ELM) to implement fault diagnosis.

2. Motion Estimation of Image Block Matching Based on Diamond Search

Block matching motion estimation algorithm is most widely used motion estimation algorithm. As shown in Figure 1, the basic idea of motion estimation based on block matching is that each frame of the image sequence is divided into a lot of nonoverlapping blocks, and it is believed that all the pixels in the block have the same characteristics. Then, for each block in current frame, we used a certain matching criterion and searched for the most similar one with the current block whose range is given by previous frame image. Therefore, motion displacement which is calculated by the relative position between match block and current block is motion vector of current block between two frames.

Generally, block size is $M \times N$, and search range is determined by maximum offset. If maximum offset vector is (dX_{\max}, dY_{\max}) , search area is $(M + 2 \times dX_{\max}, N + 2 \times dY_{\max})$. Commonly, the best match criteria are minimum of absolute error and sum of absolute difference (SAD). Calculation formula of SAD is

$$\text{SAD}(i, j) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} |f_n(x, y) - f_{n-1}(x+i, y+j)|, \quad (1)$$

where (i, j) is component product of displacement vector in horizontal and vertical axis and f_n and f_{n-1} are pixel value of current frame and reference frame.

The highest accuracy of block matching motion estimation algorithm is in full search, in which each pixel within its scope is matching search operation to obtain an optimal motion vector. However, the computational complexity is too high; when the block and search area are large, the speed is very slow; so, this is not suitable for detection of breaker trajectory image rapidly. There are three-step, four-step, and diamond search algorithm used in fast block matching motion estimation algorithm [21]. Based on the theoretical and experimental comparison, this paper uses diamond search algorithm of image block motion estimation and search process is as follows [22]:

- (1) At first, for maximum search range of seven, the algorithm builds a 5×5 window which takes the starting point as the center and calculated matching error of nine points as shown in Figure 2(a). If the minimum matching error is center point, jump to (3); otherwise jump to (2).
- (2) Take the minimum matching error point as new window center and build a new 5×5 window.

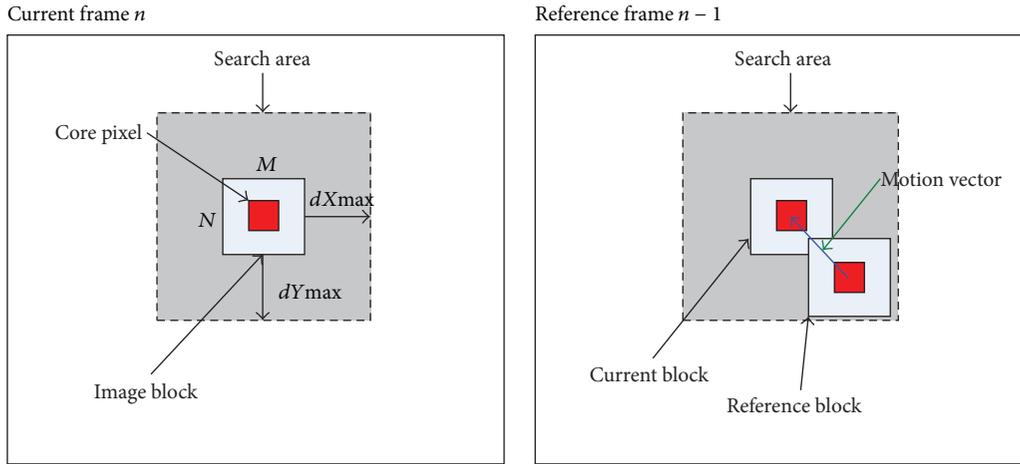


FIGURE 1: Diagram of motion estimation based on block matching.

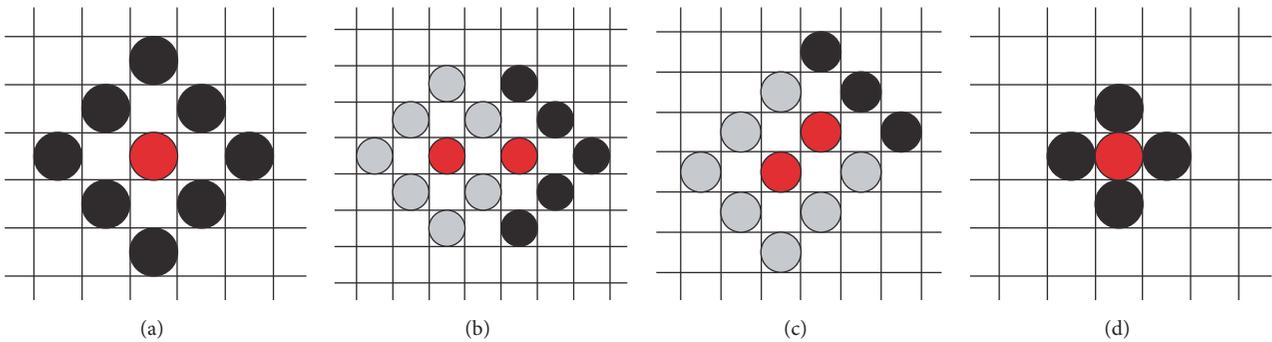


FIGURE 2: Diagram of diamond search for block matching motion estimation.

- (i) If the minimum matching error point is tetragon, calculate match error of five black points in new window as shown in Figure 2(b) and find the minimum matching error point.
- (ii) If the minimum matching error point is mid-point of four sides, calculate match error of three black points in new window as shown in Figure 2(c). If matching errors of these points are larger compared to the center point, jump to (3); otherwise, jump to (2).
- (3) Search window is reduced to 3×3 , calculate match error of five points in Figure 2(d), and find the minimum matching error point, which is the final search result.

3. Moving Contact Tracking and Analysis

3.1. *Trajectory Tracking of Moving Contact.* In this paper, we build a set of circuit breaker operating mechanisms of mechanical properties testing system. When the system tests mechanical characteristics of circuit breaker operating mechanism, the accuracy such as travel can reach 0.05 mm, and action time can be accurate to millisecond.

We take LW59-252/4000-50 as test object, which is 220 kV sulfur hexafluoride circuit breaker. Then, we use high-speed camera to get breaker operating image sequence of circuit breaker open and close. In test process, insulated pull rod and the spindle auxiliary markers are both linked movable contact, partial images of the linear and rotary motion as shown in Figures 3(a) and 3(b), respectively.

Mechanical parameters of circuit breaker can be calculated by travel-time curve. Upon circuit breaker closing, moving contact will move quickly and contact static contact, making circuit breaker conduction with connection to the load. However, due to inertia, moving contact will move to the highest point and then return to equilibrium point, which will form an overshoot process. Therefore, the travel curve of circuit breaker exhibits an overshoot process. Figure 4 shows the method of circuit breaker mechanical characteristic parameters which are defined and calculated based on circuit breaker travel-time curve.

With diamond block matching algorithm, we can track pull rod and spindle auxiliary markers and obtain moving contact travel-time curve of circuit breaker. Figure 5 shows calculation of breaker travel-time curve according to auxiliary marker centroid line of rotational angle in the process of circuit breakers motion. As the spindle movement is rigid body rotation, two-auxiliary marker centroid connection

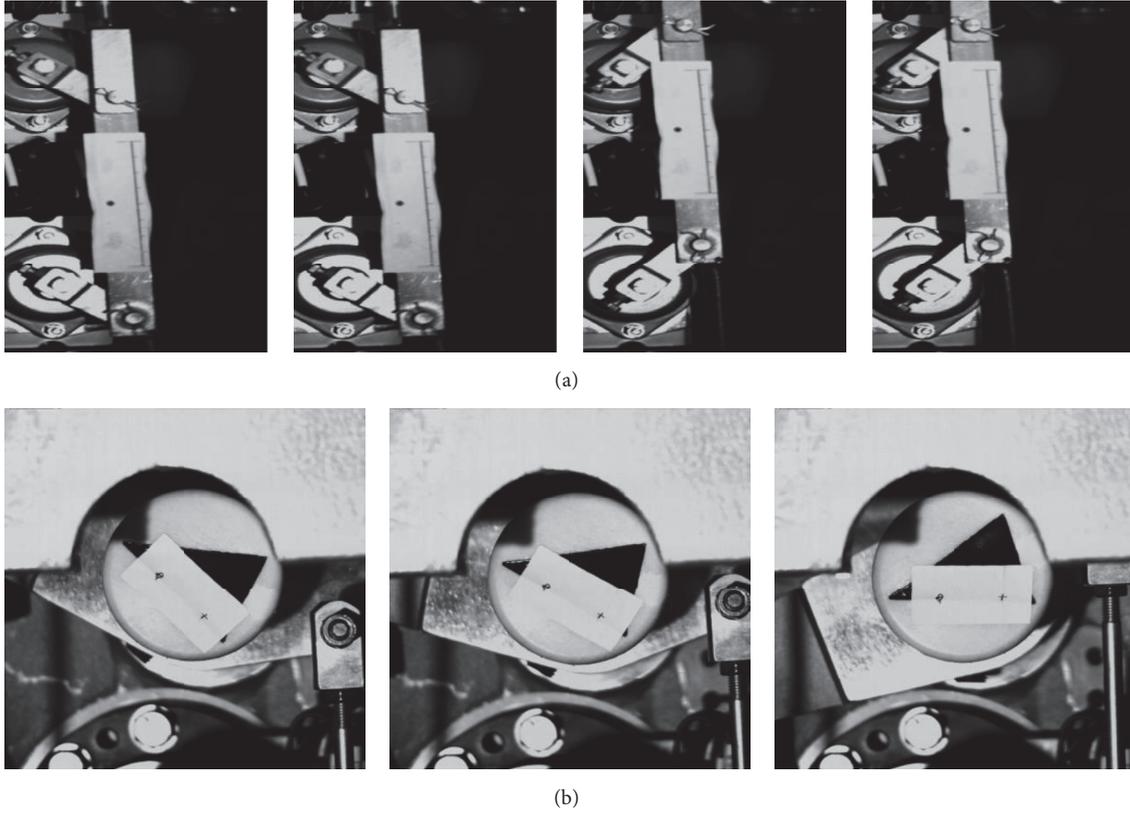


FIGURE 3: Partial images of auxiliary marker when the breaker is actioned: (a) linear motion of auxiliary markers on insulated pull rod and (b) rotary motion of auxiliary markers on principal axis.

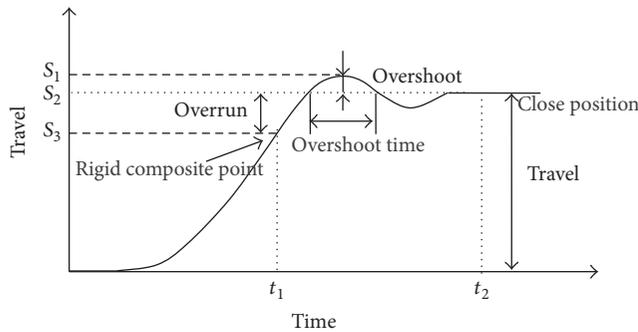


FIGURE 4: Diagram of travel-time curve and mechanical parameters definition and calculation method of circuit breaker.

rotation angle is spindle rotation angle, which reflects circuit breaker moving contact angular displacement characteristics indirectly.

Before action, assume the connection between centroid of auxiliary marker is l_1 . After action, it is l_2 . Then, the angle θ from l_1 to l_2 is angular displacement of the moving contact, where $\theta \in [0, \pi)$, and the computation formula is

$$tg\theta = \frac{k_2 - k_1}{1 + k_2 \times k_1}, \quad (2)$$

where k_1 and k_2 are the slope of line l_1 and l_2 .

Use the formula to calculate the angular displacement provided that l_1 and l_2 are present. If slope of both l_1 and l_2 does not exist, then l_1 and l_2 are parallel, and angular displacement θ is 0. When only one slope does not exist, there are four cases:

- (1) If slope of l_1 does not exist and the angle between horizontal axis and l_1 is $\alpha_1 < \pi/2$, then $\theta = \pi/2 - \alpha_1$.
- (2) If slope of l_1 does not exist and the angle between the horizontal axis and l_1 is $\alpha_1 > \pi/2$, then $\theta = \pi/2 + (\pi - \alpha_1)$.
- (3) If slope of l_1 does not exist and the angle between the horizontal axis and l_1 is $\alpha_2 < \pi/2$, then $\theta = \alpha_2 + \pi/2$.
- (4) If slope of l_1 does not exist and the angle between the horizontal axis and l_1 is $\alpha_2 > \pi/2$, then $\theta = \alpha_2 - \pi/2$.

Using diamond search algorithm, we track linear motion of auxiliary marker and obtain centroid motion trajectory in x -axis and y -axis as shown in Figure 6.

Tracking spindle two auxiliary marks, we can obtain motion trajectory of the centroid in x -axis and y -axis, respectively, as shown in Figures 7(a) and 7(b). The motion synthesis is carried out on image plane as shown in Figure 7(c). With pull rod and motion trajectory of the auxiliary marks in shaft, internal, and external parameters of camera and frame rate, we can get circuit breaker travel-time curve.

TABLE 1: Measurement result of mechanical characteristic for circuit breaker operating system.

MCP	unit	TR	FRR	GOTR	OMR
Close time	ms	90 ± 10	96	94.8	98.7
Close velocity	m/s	3.5 ± 0.6	3.63	3.92	3.07
Open time	ms	30 ± 5	34.7	34.6	34.3
Open velocity	m/s	7 ± 0.5	6.93	7.03	7.27

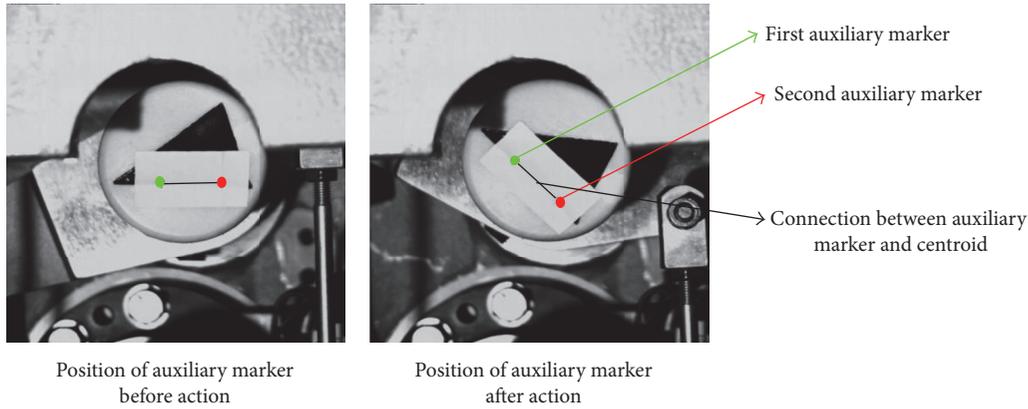


FIGURE 5: Diagram of angle displacement measurement method.

In experiment, open and close travel-time curve of LW59-252/4000-50 circuit breaker are shown in Figure 8.

From Figure 8, the noncontact measurement method is used to obtain circuit breaker travel-time curve, and we can describe moving contact trajectory of circuit breaker accurately.

3.2. Feature Extraction of Moving Contact. In order to verify the performance of our method, we compare our result with grating of tester as shown in Table 1. In Table 1, MCP denotes mechanical characteristic parameter, TR denotes technical requirement, FRR denotes factory report results, GOTR denotes grating of tester results, and OMR denotes our method results.

From Table 1, we can find it is coincident that mechanical characteristic parameters of circuit breaker open and close velocity are based on our method with current tester and conform to the requirements of factory report.

Upon HVCB fault diagnosis, time characteristics reflect the whole process of moving contact movement, which is very important for the movement of the moving contact and mechanical fault diagnosis of circuit breaker. In the paper, we test three kinds of states including normal state, mechanism jam, and operating mechanism loosening, where three sets of motion features extracted from various states are extracted as Table 2. In Table 2, CHV denotes characteristic value, MT denotes movement time, CD denotes contact distance, OT denotes observation travel, OS denotes overshoot, OV denotes overtravel, and CV denotes close velocity.

4. Fault Diagnosis of Circuit Breaker Based on ELM

4.1. Extreme Learning Machine. ELM is a simple, easy-to-use, and effective single hidden layer feedforward neural network learning algorithm. Traditional neural network learning algorithms (e.g., BP algorithm) need to set up a large number of network training parameters, and it is easy to generate local optimal solution. ELM network only needs to set number of hidden nodes but does not require the network to adjust the input weights and hidden element of bias in the whole algorithm implementation process [23–27]. Different from network weights iterative adjustment strategy of traditional neural network training method, ELM complete network training process with the novel way of solving linear equations, avoid cumbersome adjustment of neural network parameter in iterative process, and enhance training speed of neural network greatly. Compared to popular machine learning methods, ELM has the merits of easy structure and strong learning and generalization ability. Therefore, we construct circuit breakers fault diagnosis model based on ELM, which can improve diagnosis accuracy and computational efficiency greatly.

For n different samples (x_i, t_i) , $i = 1, 2, \dots, n$, N is the number of hidden nodes, excitation function $g(x)$ of the standard single hidden layer feedforward neural network is able to approximate n samples without error, which implies β_i , w_i , and b_i satisfy

$$\sum_{i=1}^N \beta_i g(w_i \cdot x_j + b_i) = t_j \quad j = 1, \dots, N, \quad (3)$$

TABLE 2: Feature extraction of circuit breaker in various conditions.

Status	CHV					
	MT (ms)	CD (mm)	OT (mm)	OS (mm)	OV (mm)	CV (m/s)
Normal close	96.182	15.277	133.621	3.206	118.344	3.42
	96.706	15.125	132.317	2.891	117.192	3.61
	97.237	14.324	132.695	2.796	118.371	3.29
Mechanism jam	79.385	8.468	108.219	1.895	99.751	2.81
	77.184	8.652	110.547	1.589	101.895	3.05
	85.982	10.626	122.524	1.967	111.898	2.58
Operating mechanism loosening	102.546	11.338	140.845	2.166	129.507	2.34
	110.361	12.466	145.784	2.452	133.318	2.35
	115.962	12.989	148.866	2.578	135.877	2.35

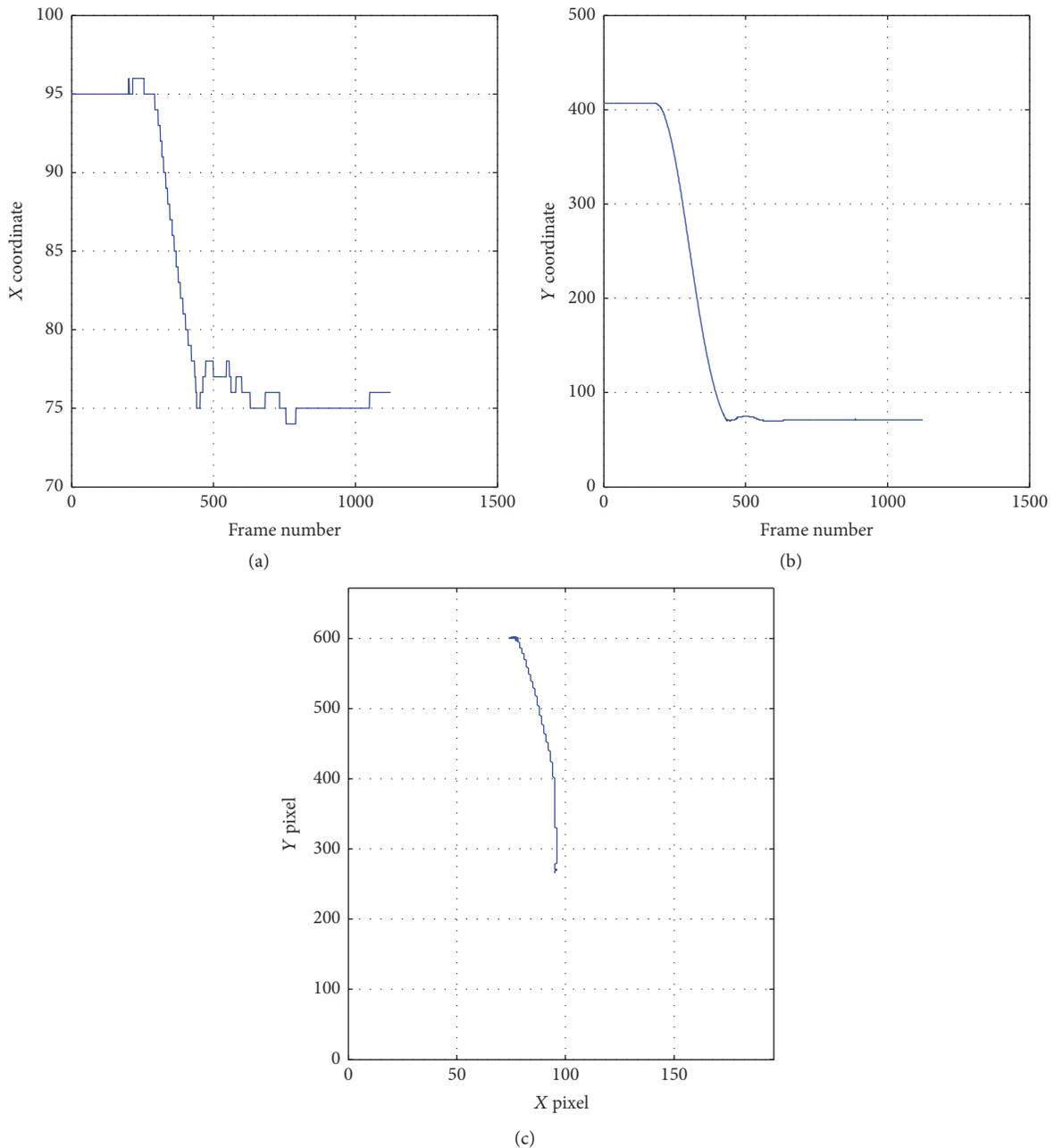


FIGURE 6: Motion trajectory of the auxiliary marker on the pull rod of breaker.

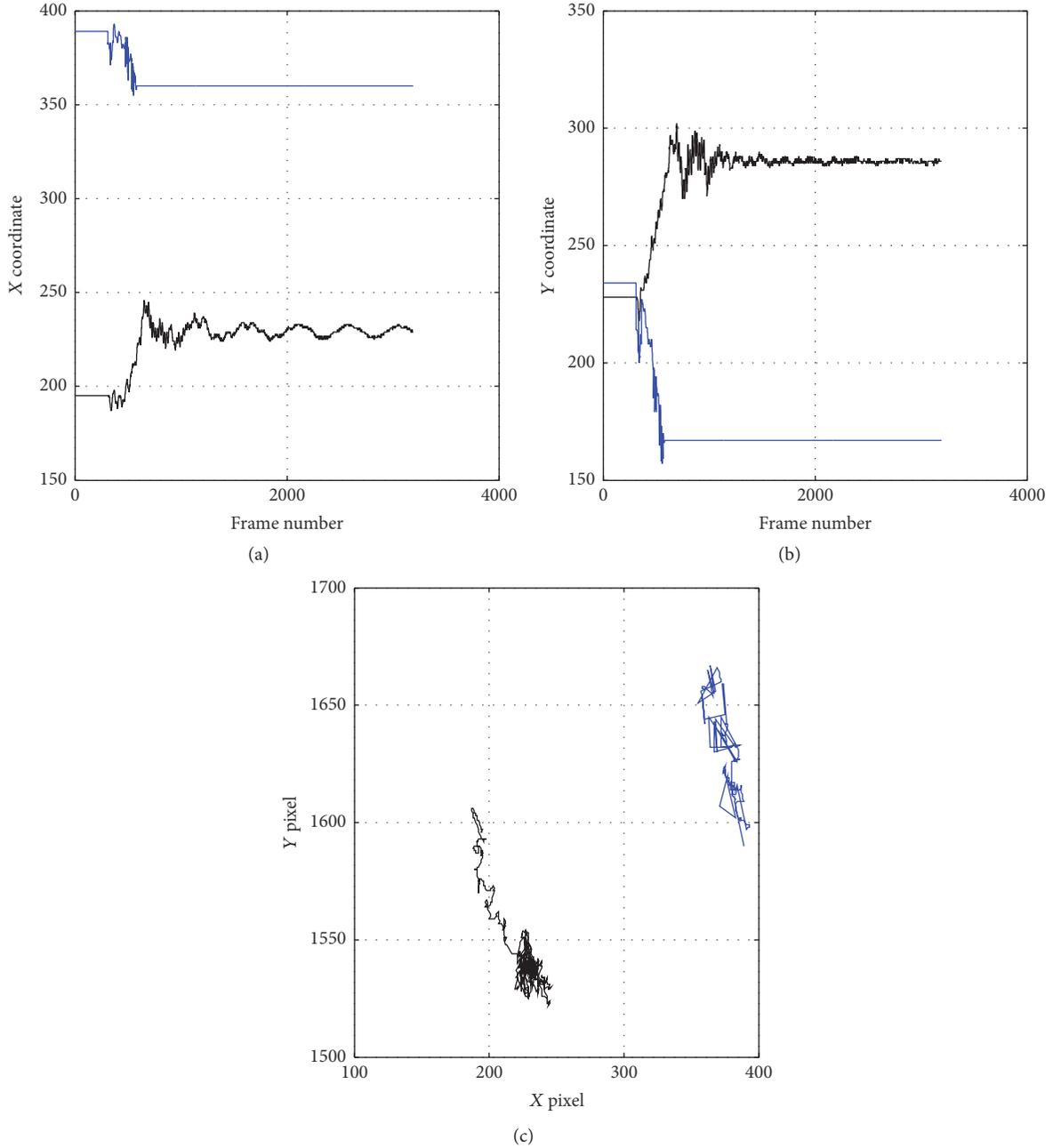


FIGURE 7: Motion trajectory of the two auxiliary markers on the shaft of breaker: (a) x-axis motion trajectory, (b) y-axis motion trajectory, and (c) motion trajectory of auxiliary marker.

where $w_i = (w_{i1}, w_{i2}, \dots, w_{in})^T$ is connected to the i th hidden nodes and weights of input nodes, $\beta_i = (\beta_{i1}, \beta_{i2}, \dots, \beta_{im})^T$ is connected to the i th hidden nodes and weights of output nodes, and b_i is threshold of the i th hidden nodes.

Equation (3) can be expressed by matrix as

$$H\beta = T, \tag{4}$$

where

$$H(w_1, \dots, w_N, b_1, \dots, b_N, x_1, \dots, x_n) = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \cdots & g(w_N \cdot x_1 + b_N) \\ \vdots & & \vdots \\ g(w_1 \cdot x_n + b_1) & \cdots & g(w_N \cdot x_n + b_N) \end{bmatrix},$$

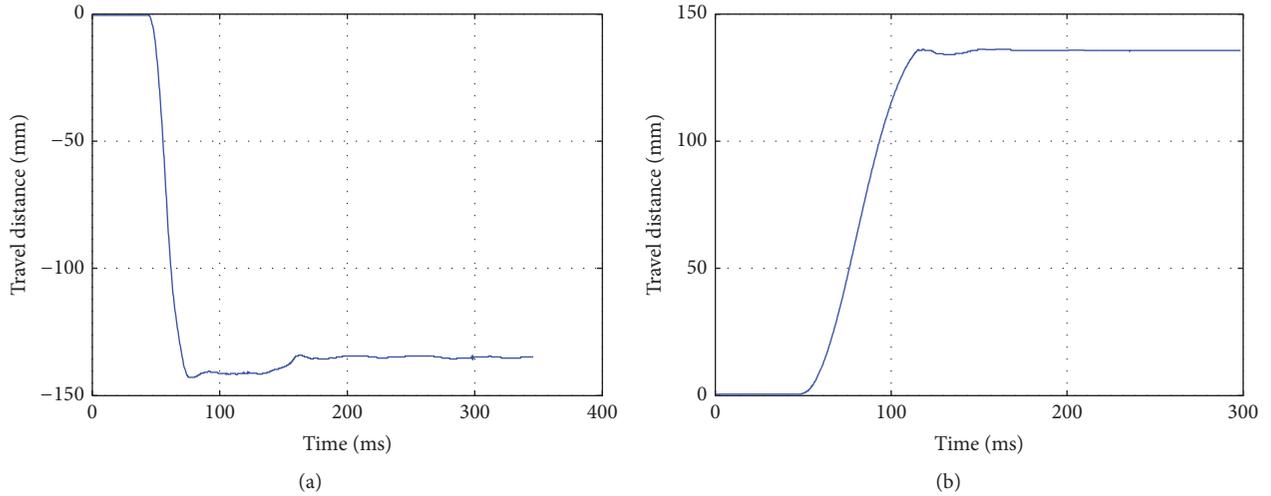


FIGURE 8: Travel-time curve of circuit breaker: (a) open and (b) close.

$$\begin{aligned}\beta &= [\beta_1^T, \dots, \beta_N^T]_{N \times m}^T, \\ T &= [t_1^T, \dots, t_n^T]_{n \times m}^T.\end{aligned}\quad (5)$$

Matrix H is called output matrix of neural network, and the i th column is the output of the i th hidden layer node affected by inputs x_1, \dots, x_n .

According to the theory of ELM, once the learning begins, the input weights w_i and hidden layer threshold b_i need not be adjusted, and the hidden layer output matrix H can be kept unchanged. From (4), we can see that the problem is simply equivalent to the least square solution $\hat{\beta}$ of a linear system $H\beta = T$. However, if the matrix H is not a square matrix, w_i , b_i , and β ($i = 1, \dots, N$) do not exist, satisfying the linear system $H\beta = T$.

Therefore, the minimum norm least square solution of the above linear system should be expressed as

$$\hat{\beta} = H^{-1}T, \quad (6)$$

where H^{-1} is a generalized inverse matrix of matrix H .

4.2. Steps of Fault Diagnosis. According to the above principle, the fault diagnosis method of HVCB based on ELM is as follows:

- (1) Obtaining motion trajectory of moving contact motion.
- (2) According to motion trajectory, calculating characteristic value samples, such as movement time, contact distance, observation travel, overshoot, over-travel, and close velocity.
- (3) Taking six characteristic values as inputs of ELM, determining hidden neurons layer numbers N , setting the connection weights w_i hidden layer neuron threshold b_i between input layer and implicit layer, and calculating the weights $\hat{\beta}$ of the output layer randomly and using trained ELM to realize circuit breaker mechanical fault diagnosis and classification.

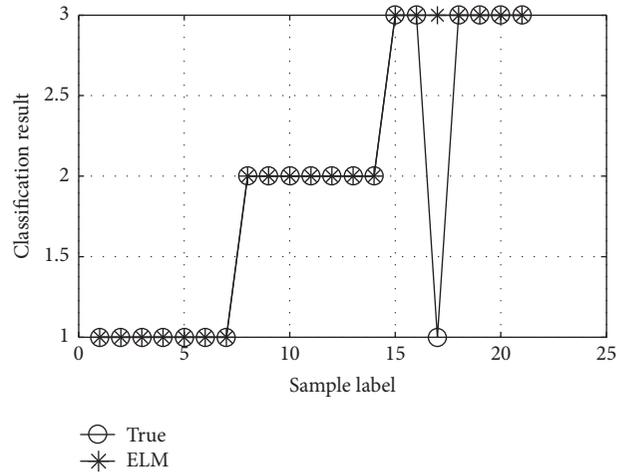


FIGURE 9: Comparison of classification results.

4.3. Experiment Analysis. In practical test, we use operation of LW59-252 as study object and collect three statuses of normal close status, mechanism jam, and operating mechanism loosening.

20 groups of each state's data are collected, then the input of the ELM is constructed according to the selected feature vector, and the sample data is divided into training set and test set into the ELM for the purpose of state recognition and classification. In this paper, single hidden layer neural network is set up with 6 characteristic values as inputs.

We select 2/3 of data of every state as training data, and 1/3 of data is used as test data. Labels of three types are 1, 2, and 3 and they express normal close status, mechanism jam, and operating mechanism loosening, respectively. In experiment, numbers of test data are as follows: 1~7 indicate normal close status, 8~14 indicate mechanism jam, and 15~21 indicate operating mechanism loosening. The results of classification and comparison are shown in Figure 9.

From Figure 9, we can get the proposed method can analyze state of circuit breaker very well. Accuracy rates

TABLE 3: Analysis of classification results of different models.

Model	MAPE/%	RMSE	MAE	Convergence time/s
BPNN	7.2431	0.0892	0.2465	1.0611
SVM	8.1470	0.0987	0.2823	0.7136
ELM	4.6349	0.0485	0.1404	0.2534

in analysis of normal close status and mechanism jam are 100% and in analysis of operating mechanism loosening there appears an error, so the overall correct rate is 95.23%. Fault diagnosis of circuit breaker in the process of miscarriage of justice is mainly due to the fact that operating mechanism loosening is very weak; thus, the motion trajectory of HVCB is very similar to normal close status, causing a miscarriage of justice. Therefore, if we unite other signals to diagnose fault of HVCB, we will get higher accuracy rate.

To further verify performance of our method, we compared BPNN, SVM, and ELM model for the same circuit breaker moving contact data and the compared results are shown in Table 1. In our experiments, BPNN model used 3 layers' structure, 15 input nodes, 31 hidden layer neurons, 1 output node, activation function is Sigmoid function, and learning rate is 0.01; SVM model obtained the regularization parameter with cross validation strategy, kernel function is radial basis function (RBF), optimization of SVM network parameters is genetic algorithm (GA), penalty parameter $c = 100$, and kernel function $\sigma = 1.52$. Neurons number in hidden layer of ELM model is 8 and activation function is Sigmoid function. Convergence time and classification accuracy of the three models are shown in Table 3, where classification accuracy is mean absolute percentage error (MAPE), root mean squared error (RMSE), and mean absolute error (MAE).

In Table 3, we can find that ELM model obtains faster convergence time and higher prediction precision compared with BPNN and SVM model. Under the same conditions, compared with BPNN, evaluation indexes MAPE and RMSE and MAE and convergence time decreased by 36%, 45.63%, 43.04%, and 76.12%, respectively; compared with SVM, evaluation indexes MAPE and RMSE and MAE and convergence time decreased by 43.11%, 50.86%, 50.27%, and 64.49%, respectively. Therefore, fault diagnosis method based on diamond search and ELM can diagnose the circuit breaker with moving contact movement characteristics and obtain high accuracy diagnostic results.

5. Conclusion

In order to avoid the disadvantages of traditional HVCB mechanical characteristic detection method, this paper presents a new method of noncontact visual inspection based on diamond image block matching. The mechanical characteristics of circuit breaker operating mechanism are analyzed by analyzing the image sequence of auxiliary markers motion on pull rod and spindle moving contact with high-speed and high-resolution camera. Then, according to motion trajectory, we calculate characteristic value samples, such as movement time, contact distance, observation travel,

overshoot, overtravel, and close velocity and construct evaluation model making use of the six characteristic values as inputs of ELM. Our method has the following characteristics: (1) it is a kind of noncontact measurement method based on visual analysis, which does not need to be connected with the circuit breaker in electrical and physical connection, so it facilitates site operation and testing. (2) This method not only can obtain linear displacement time curve of the moving contact but also can obtain the time curve of the angular displacement. (3) Using high-speed, high-definition camera can get circuit breaker operating mechanism action subtle and continuous change and moving contact space and time motion characteristics measurement speed and accuracy are greatly improved. (4) Fourth characteristic is making use of ELM for fault diagnosis and classification, which can overcome inconvenience of enormous training data in traditional neural network and setting multiple parameter in SVM.

Competing Interests

The authors declare that they have no competing interests.

Acknowledgments

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