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Surface Defects Detection and Identification of Lithium Battery Pole Piece Based on Multi-Feature Fusion and PSO-SVM

CHANGLU XU, LINSHENG LI, JIWEI LI, AND CHUANBO WEN
School of Electrical Engineering, Shanghai Dianji University, Shanghai 201306, China

Corresponding author: Linsheng Li (lils@sdju.edu.cn)

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ABSTRACT In order to realize the automatic detection of surface defects of lithium battery pole piece, a method for detection and identification of surface defects of lithium battery pole piece based on multi-feature fusion and PSO-SVM was proposed in this paper. Firstly, image subtraction and contrast adjustment were used to preprocess the defect image to weaken the influence of non-defective areas and enhance the defect features. Then, Canny algorithm and the AND logical operation were used to extract the image of defect area. Next, the texture feature, edge feature, and HOG feature were combined to extract the feature of the defect area image. Finally, the support vector machine (SVM) optimized by particle swarm optimization (PSO) was used to automatically identify and classify defect images. The experimental results show that the proposed method in this paper can effectively detect surface multiple types defects of lithium battery pole piece, and the average recognition rate of defects reaches 98.3%, which is an effective and feasible automatic defect detection and identification method.

INDEX TERMS Machine vision, surface defects of lithium battery pole piece, defect detection, support vector machine, defect segmentation.

I. INTRODUCTION

As a key component of lithium battery manufacturing, lithium battery pole piece is prone to surface defects in the production process of slurry preparation, slurry coating and roll pressure [1]–[3], which will have an adverse impact the capacity, cycle life, and safety of lithium batteries [4]–[7]. Therefore, it is necessary to detect the surface defects of lithium battery pole piece. Compared with the traditional defect detection methods, machine vision has the advantages of non-contact, non-destructive, real-time detection and safety, which provides a new way for surface defects detection of lithium battery pole piece [8].

A method of systematically collecting and classifying the pole piece defects generated in the calendering process was proposed in literature [9]. This method can reduce the cost by reducing the reject rate in the production process. A structure segmentation algorithm based on image data is proposed in literature [10], which can detect the defects in the particle system and identify fragments of the same particle by segmenting individual particles. The algorithm is used to detect and identify defects of fault image data of lithium battery anode and cathode, and shows wide applicability to data sets with different defects and reasonable size ranges. A new method that combines smart camera with graphics and virtual programming software LabVIEW to inspect defects of the pole piece was proposed in literature [11]. The method combines hardware and software to improve the efficiency of electrode defect detection. The characteristics of the pole piece defects of Li-ion Power battery were described in detail and morphological characteristics were analyzed in literature [12], which was helpful to the subsequent image processing and the production practice. A method of combining pulse thermal imaging cameras and image processing algorithms to detect and identify defects on the pole piece film was proposed in literature [13]. This method is suitable for practical production. A noise-resistant and multi-resolution version of LBP was proposed in literature [14] that extracted color/texture features jointly. And a new surface defect detection method was proposed based on this algorithm, which used to the defect detection of architectonic stone and patterned fabric. This method has the advantages

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of high detection rate, low computational complexity, low noise sensitivity. A segmentation-based deep-learning architecture was proposed in literature [15] that was designed for the detection and segmentation of surface anomalies. This method uses a small number of defective surfaces for learning, making deep learning methods can be used in industries with limited number of defective samples. An effective similarity measurement method was proposed in literature [16], which used the adjoint matrix of two comparison images to calculate the symmetric matrix, and used the rank of the symmetric matrix as the similarity measurement index of defect detection. The method is simple in calculation and can be used for detection of defects on the material surfaces, PCB, ceramic tiles, fabrics and integrated circuit boards.

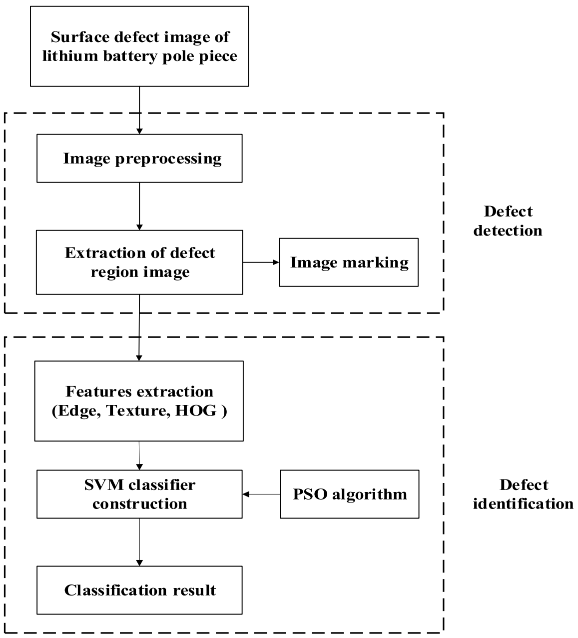

FIGURE 1. **The flow chart of the overall idea.**

This paper presents a method for detection and identification of surface defects of lithium battery pole piece. The overall process of this method is shown in Figure 1, which is mainly composed of two stages: defect detection and defect identification. In the defect detection stage, image subtraction [17] and contrast adjustment are firstly used to preprocess the input image to weaken the interference of non-defect areas and enhance defect features. Then, through Canny edge detection algorithm [18] and the AND logical operation [19] processing, the defect area image is extracted from the lithium battery pole piece, and the defect detection is completed by combining image labeling. In the defect identification stage, the texture features, edge features and HOG features are extracted from the defect area image, and entered into the support vector machine classifier optimized by the particle swarm algorithm in order to achieve the purpose of identifying the defect image.

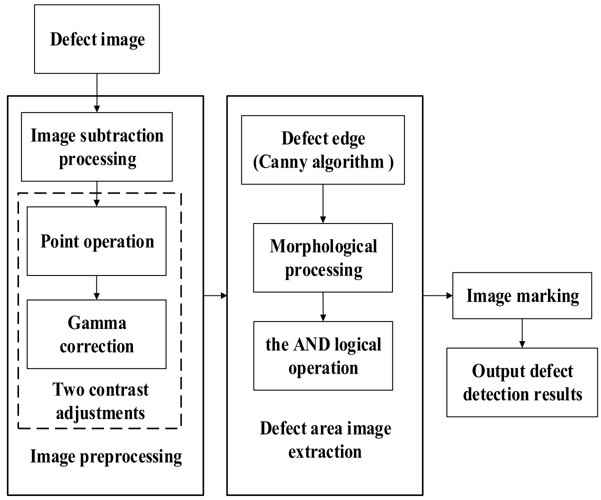

FIGURE 2. **The surface defects detection process of lithium battery pole piece.**

II. SURFACE DEFECTS DETECTION OF LITHIUM BATTERY POLE PIECE

The surface defects detection process of lithium battery pole piece is shown in Figure 2, which is mainly composed of image preprocessing and extraction of defect area image. In the process of image preprocessing, image subtraction is used to preliminarily extract defect image. Then the method of two contrast adjustments is used to weaken the interference in non-defect areas. Finally, the AND logical operation is used to complete the extraction of the defect area image, and the defect detection is realized by combining the image marking.

A. IMAGE PREPROCESSING

In the process of lithium battery pole piece image acquisition, it is easy to be affected by the shooting angle and the lighting environment, which may cause some interferences. At the same time, the defect itself also has the problems of different gray levels and blurred edges. In addition, the overall contrast of lithium battery pole piece image is low, the gray difference between some defects and the normal area is small, and there is the influence of non-defect traces, which makes it difficult for traditional image segmentation algorithm to extract the complete defect area image. In order to solve these problems, a method based on image subtraction and contrast adjustment is proposed in this paper to preprocess defect images.

The breakage defect is taken as an example in this paper, and the result of image subtraction processing is shown in Figure 3. The surface defect image of the lithium battery pole piece is compared with the template image by image subtraction, and the defect area image is extracted preliminarily. However, due to the low overall contrast of the image, the non-defective part brings great interference to the extraction of the defect area. To solve this problem, this paper adopts the method of two contrast adjustments for processing, as shown in Figure 4.

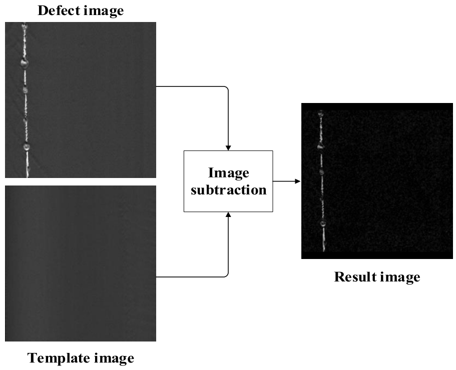

FIGURE 3. Image subtraction processing.

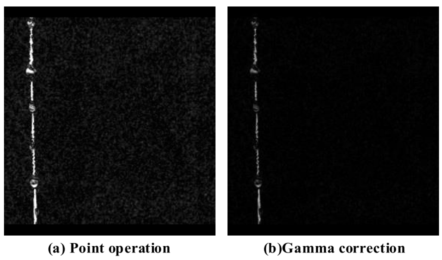

FIGURE 4. Two contrast adjustment processing.

The result of the first contrast adjustment is shown in Figure 4 (a). The overall contrast of the image is improved through dot operation to increase the difference between the defective area and the non-defective area. Figure 4 (b) is the result of the second contrast adjustment. The gray level of the brighter area of the image is compressed by the method of Gamma correction [20], and the gray level of the darker area of the image is stretched, so as to retain the defect area and weaken the influence of the non-defect part.

B. IMAGE EXTRACTION OF DEFECT AREA

The defect area image extraction is composed of edge detection, morphological processing and the AND logical operation. Figure 5 shows the result of defect edge detection, which obtains the edge contour of the defect through the Canny edge detection algorithm. However, there are a small number of non-defective parts in the defect area, resulting in partial edge missing, which will reduce the accuracy of defect detection. To solve this problem, morphological processing is used to fill the extracted defect contours, as shown in Figure 6 (a). Then, the AND logical operation is carried out in Figure 6 (a) and Figure 6 (b) to extract images of defect areas. Figure 6 (c) shows the extracted defect area image.

III. SURFACE DEFECTS IDENTIFICATION OF LITHIUM BATTERY POLE PIECE

This paper analyzes the appearance representation of defects and the differences among various defects, and the gray level co-occurrence matrix, Sobel algorithm and HOG algorithm are selected to extract the texture features, edge features and HOG features of images. Then, the extracted features are input into the support vector machine optimized by particle swarm optimization algorithm to realize the identification and classification of the surface defects of lithium battery pole piece.

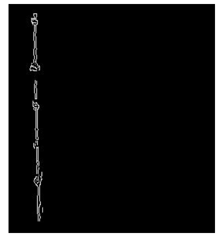

FIGURE 5. Edge detection.

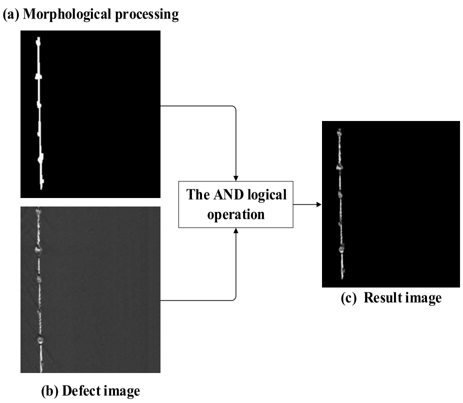

FIGURE 6. The AND logical operation.

A. SUPPORT VECTOR MACHINE

Support vector machine [21] is a supervised learning method based on statistical learning theory. Following the principle of structural risk minimization, it is suitable for dealing with small sample problems and has been widely used in the field of statistical classification and regression analysis [22]. The defect image data of lithium battery pole piece is limited. Therefore, the support vector machine algorithm is selected to identify and classify the surface defects of lithium battery pole piece. Support vector machine adopts radial basis kernel function, and the decision function for classifying of the feature vector is expressed as Equation (1) [23] and Equation (2) [24]:

$$f(s) = sign(\sum_{i=1}^{N} \alpha(i) y_{wr}(i) \kappa(S(i), S) + b) \tag{1}$$

where $\alpha(i)$ is the Lagrange multiplier, N is the number of training samples, $y_{wr}(i)$ is the class label of training sample $S(i)$, and b is a bias, κ is the radial basis function (RBF) kernel.

$$\kappa(S(i), S) = \exp(-\gamma \left\| S(i) - S \right\|^2) \tag{2}$$

where γ is the kernel parameter. The above optimization problem can be reformulated by Lagrange functional:

$$\max_{\alpha}(\sum_{i=1}^{N} \alpha(i) - \frac{1}{2} \sum_{i,l=1}^{N} \alpha(i)\alpha(l) y_{wr}(i) y_{wr}(l) K(S(i), S)) \tag{3}$$

$$\text{Subject to } \sum_{i=1}^{N} \alpha(i) y_{wr}(i) = 0, \quad 0 \leq \alpha(i) \leq C \tag{4}$$

where $S(i)$ is the support vector corresponding to a nonzero $\alpha(i)$, and C is regularization constant. In this paper, the regularization parameter C and kernel parameter γ are optimized by particle swarm optimization algorithm.

B. PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization algorithm is a global random search algorithm based on swarm cooperation developed by simulating the foraging behavior of birds and fish [25]. The principle of the particle swarm optimization algorithm is to initialize the particles randomly, then search for the optimal solution by updating each generation of particles, and search for the best position according to the optimal solution. In each iteration, each particle moves in the direction of the best individual and the best global position. In the multi-dimensional space search process, each particle moves according to Equation (5) and Equation (6):

$$v_{in}(t) = w_i \times v_{in}(t-1) + c_1 \times rand1() \times (p_{in} - x_{in}(t-1)) + c_2 \times rand2() \times (p_{gn} - x_{in}(t-1)) \tag{5}$$

$$x_{in}(t) = x_{in}(t-1) + v_{in}(t) \tag{6}$$

where w_i represents the weight of inertia, c_1 and c_2 are two constants for adjusting acceleration, $rand1$ and $rand2$ are random numbers evenly distributed in (0,1).

C. DEFECT FEATURE EXTRACTION

Due to some surface defect features of lithium battery pole pieces are not obvious enough, and there are some interferences from non-defect traces, the accuracy of single feature in defect recognition is low. To this end, this paper starts with the multi-feature directions, and firstly obtains texture feature, edge feature and HOG feature from the extracted defect area image. Then, principal component analysis (PCA) is used to reduce the dimension of edge feature with higher feature dimensions. Finally, edge feature, texture feature and HOG feature are serially fused as the combined feature of defect identification.

Gray level co-occurrence matrix is a statistical image analysis method, which is widely used in image detection and classification by extracting texture features [26], [27]. The texture of different types of defects has certain differences, so the texture feature can be used as one of the important features of defect image classification. In this paper, four characteristic parameters, such as contrast, entropy, inverse variance and energy, are selected as texture features for defect identification by comprehensively considering the appearance characteristics of lithium battery electrode surface defects and the properties of related parameters of gray level co-occurrence matrix. In order to reduce the amount of matrix calculation, this paper uses four directions ($0°$, $45°$, $90°$, $135°$) for calculation when building the gray-level co-occurrence matrix.

Sobel algorithm is an edge detection operator based on the first derivative. It combines differential derivation and averaging factor, not only has a good edge contour detection effect, but also has a smooth suppression effect on noise, and is mainly used for edge detection [28]. The edge of the surface defects of the lithium battery pole piece shows obvious difference, which makes the edge feature can express the characteristic information of the defect. Therefore, this paper comprehensively considers the accuracy and efficiency of edge detection, and selects Sobel algorithm to obtain the defect edge as the edge feature of the defect.

HOG feature is a kind of feature descriptor, which forms the feature by calculating and counting the gradient direction histogram of the local area of the image [29]. It can well describe the characteristics of the local target region, and its characteristic is that it can keep good invariance to the geometric and optical deformation of the image. Therefore, this paper uses HOG feature to describe the local features of defects.

D. THE PSO-SVM CLASSIFICATION METHOD

This section introduces the method of classification the surface defects of lithium battery pole piece. Radial basis kernel function is adopted in the SVM algorithm. Particle swarm optimization algorithm is used to optimize the penalty parameter C and kernel parameter γ of the SVM algorithm, so as to improve the surface defect identification accuracy of lithium battery. The identification and classification steps of the PSO-SVM classifier are as follows:

1) Prepare training and test data sets for surface defects of lithium battery pole piece.

2) Particle swarm algorithm parameter setting. Including the number of particles, the number of iterations, local and global learning factors, inertia weights and optimization parameters (C, γ) value range, used for fitness calculation.

3) Particle initialization and iteration number initialization. Randomly initializes the velocity and position of each particle. Set the iteration number to zero.

4) Update the number of iterations, and repeat Steps 5) to Steps 8).

5) SVM model construction:

(a) Input feature preparation: the texture, edge and HOG feature are extracted from the defect area image, and the extracted feature is used as the input feature vector of SVM classifier.

(b) Calculate the accuracy of defect recognition: select gauss radial base core function, and use 5-fold cross-validation method to calculate the average recognition accuracy of the training set. The parameters (C, γ) are evaluated based on the recognition accuracy.

6) Calculate the fitness value of each particle.

7) Evaluate the fitness value to calculate the global optimum and update the current particle velocity and position according to Equations (5) and (6).

8) Stop the algorithm: If the termination condition is met (the deviation between the two generations meets the minimum threshold), otherwise return to Step 4.

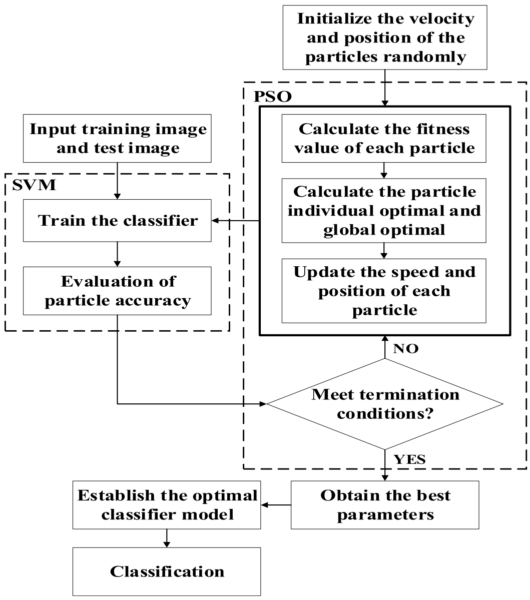

FIGURE 7. Flow chart of PSO-SVM classification method.

9) If the number of iterations reaches the predetermined maximum number of iterations, the iteration is terminated and the optimal parameters (C, γ) are output.

The flow of PSO-SVM classification method is shown in Figure 7.

IV. EXPERIMENTS AND ANALYSIS

A. DATA SET

The image data in this paper is the surface defect image of lithium battery pole piece collected by an enterprise. Considering the speed and accuracy of the detection and identification of the surface defects of lithium battery pole piece, the area scan CCD camera was selected. The camera model is TXG 50, with good stability, good imaging quality and other advantages. The collection range of the defect image is the rectangular coating area, and the image resolution is 2448 × 2050 pixels. The defect images were divided into three types: indentation, decarburization, and breakage according to the professional inspectors of the enterprise. A total of 840 data sets of the surface defects of lithium battery pole pieces are collected, among which 660 are used as the training set and 180 as the test set. The numbers of main types of surface defects of lithium battery pole pieces are shown in Table 1.

B. THE DETECTION ANALYSIS OF THE SURFACE DEFECTS OF LITHIUM BATTERY POLE PIECE

In this paper, a method for surface defects detection of lithium battery pole piece is proposed by analyzing the appearance characteristics of defects, the differences between defects and the difficulties in the defect detection process. This method mainly consists of two parts. The first step uses image subtraction and contrast adjustment to initially extract defective images and weaken the interference of non-defective areas. In the second step, the Canny algorithm is used to extract the edge contour of the defect, and the filling process is performed. Then the image logic AND operation is used to extract the defect area image. Compared with the detecting abnormalities in surface textures based on single dimensional local binary patterns proposed in literature [30], the first step of the method in this paper mainly deals with the non-defect area and non-defect trace of the image, and extracts the defect image preliminarily, without involving the calculation of image feature vector. The second step is to obtain the defect contour through edge detection of the image processed above, and combine the image logic AND operation to extract the defect area image. This part not only detects the defects on the image, but also extracts the defect area from the image to prepare for the next step of image identification.

TABLE 1. The numbers of main types of surface defects of lithium battery pole piece.

Defect types	Number of training samples	Number of test samples
Indentation	220	60
Decarburization	220	60
Breakage	220	60
Total	660	180

The detection results of various types of defects using this method are shown in Figure 8 (In order to avoid the problem of incomplete box selection mark in defect area, the upper and lower defect images were processed with gray scale expansion). The experimental results show that the defect detection method proposed in this paper can accurately detect various surface defects of lithium battery pole piece. This provides a good foundation for the subsequent extraction of defect features and the realization of defect identification.

C. THE IDENTIFICATION ANALYSIS OF SURFACE DEFECTS OF LITHIUM BATTERY POLE PIECE

The texture features, edge features and HOG features of the defect area images are extracted and combined into the support vector machine optimized by particle swarm optimization algorithm to realize the identification and classification of the surface defects of lithium battery pole piece.

SVM classifier based on radial basis kernel function is trained with training set samples in this paper, and particle swarm optimization algorithm is introduced to optimize the parameters of the model. The parameter settings of the particle swarm optimization algorithm: the particle population size is 40, the inertia weight is 0.6, the acceleration constants C_1 and C_2 are 2, and the maximum number of iterations is 100. The 5-fold cross-validation method is used to calculate the classification accuracy of the PSO-SVM model, which is used as the particle fitness value of the PSO optimization algorithm.

The optimization results of SVM classifier parameters by PSO are shown in Figure 9. In the optimization process of parameters C and γ by particle swarm optimization algorithm, the fitness value converges gradually with the increase of the number of iterations,

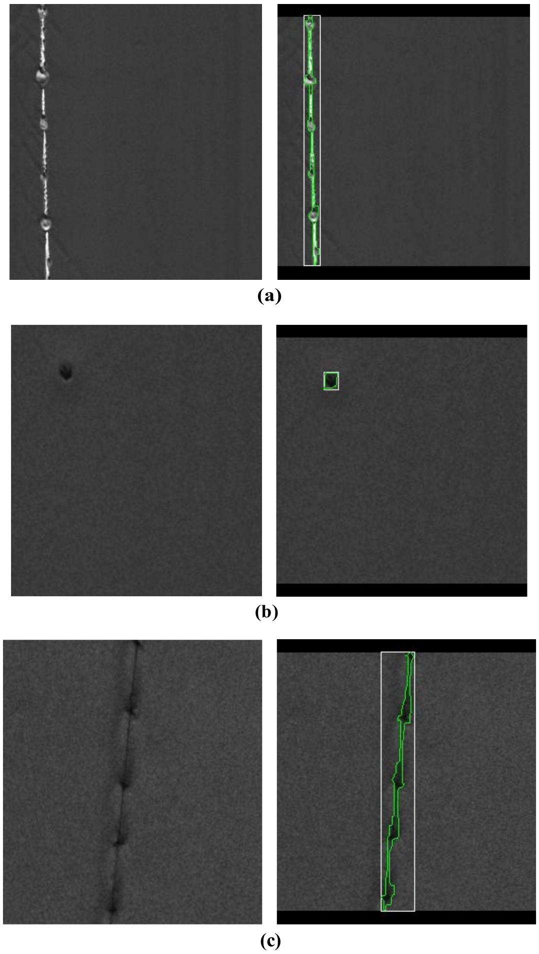

FIGURE 8. The results of each defect detection: (a) Breakage, (b) Decarburization, (c) Indentation.

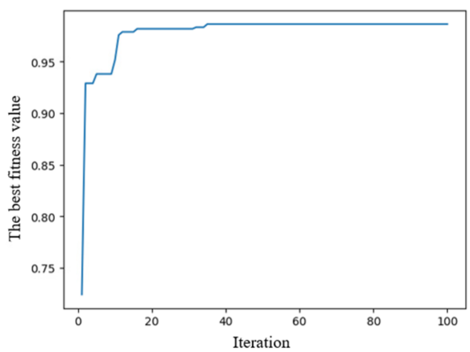

FIGURE 9. The best fitness value during the training stage.

and reaches the best value when the number of iterations is 35. The optimal parameters C $=$ 29.7516, $\gamma = 0.02738$. The trained PSO-SVM classification model is used to identify and classify the samples in the test set.

The defect identification results of single feature mode and multi-feature mode are shown in Figure 10. The experimental results show that the texture feature extracted by the gray level co-occurrence matrix has the lowest recognition accuracy, the directional gradient histogram feature extracted by HOG is

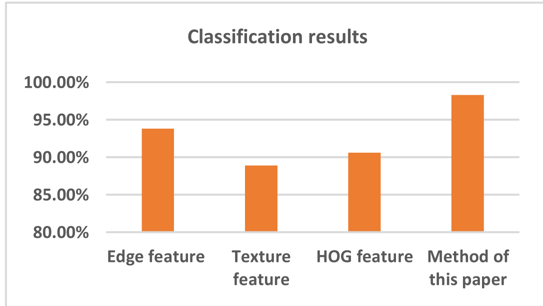

FIGURE 10. The defect recognition results of single feature mode and multi-feature mode.

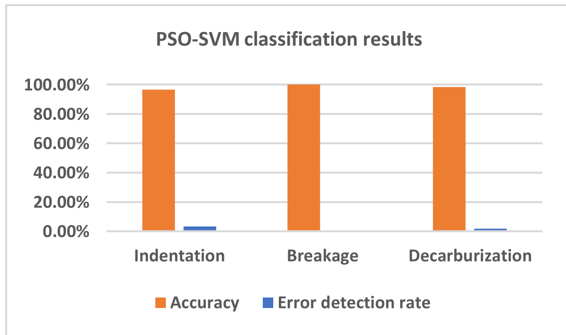

FIGURE 11. Recognition results of the PSO-SVM classification method.

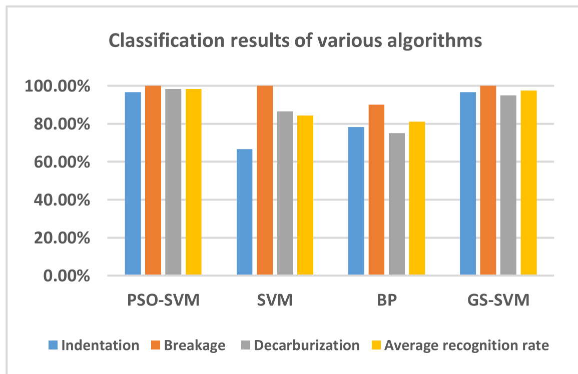

FIGURE 12. The identification results of surface defects of lithium battery pole piece by each classification method.

second, and the edge feature extracted by the Sobel algorithm has the highest recognition accuracy. It can be seen that the edge feature makes the largest contribution to the surface defect identification of lithium battery pole piece. However, in the process of defect identification, single feature can only show part of the feature information of the defect, and it is difficult to represent the whole defect comprehensively, which affects the accuracy of defect recognition. Therefore, this paper chooses to extract multiple features of the defect area image for defect identification. It can be seen from Figure 10 that the recognition accuracy of the method in this paper for defects is high, reaching 98.3%, which is significantly better than that of single feature.

The recognition results of the PSO-SVM method for the surface defects of lithium battery pole pieces are shown in Figure 11. In the defect classification experiment, a 5-fold cross-validation method was used to verify the accuracy of the method in the identification of various types of defects. The experimental results show that the PSO-SVM classification method achieves a good classification effect for multiple types of defects. The recognition rate of indentation and decarburization is 96.6% and 98%, respectively, and the recognition rate of breakage defects is the best, reaching 100%.

The classification results of various algorithms for the surface defects of lithium battery pole piece are shown in Figure 12. The neural network classifier has high requirement for the number of defect samples, but the number of defect samples obtained in this paper is limited, so the recognition accuracy of BP neural network is poor, and the average recognition rate is only 81.1%. Compared with PSO-SVM classification method and GS-SVM classification method, the SVM classifier without parameter optimization has a lower accuracy in defect recognition, with an average recognition rate of 84.4%. The PSO-SVM classification method has a recognition accuracy of over 96% for various defects, with an average recognition rate of 98.3%, which is 0.8% higher than that of GS-SVM. The experimental results show that the performance of PSO-SVM classification method is better than that of other three classifiers, and it is more suitable for the identification and classification of the surface defects of lithium battery pole piece.

V. CONCLUSION

A method of surface defects detection and identification of lithium battery pole piece based on multi-feature fusion and PSO-SVM is proposed in this paper. Firstly, a method based on subtraction operation and contrast adjustment was used to preprocess defect images to weaken the interference of non-defect areas and enhance the defect characteristics. Then, the defect area image was extracted by the Canny edge detection algorithm and the AND logical operation, and the defect detection was realized by combining the labeling processing. Finally, the surface defect features of lithium battery pole piece extracted were input into the support vector machine optimized by particle swarm optimization algorithm for training to realize the identification and classification of the surface defects of lithium battery pole piece. The experimental results show that this method can not only detect all kinds of defects accurately, but also has a high recognition rate for the surface defects of lithium battery pole piece, with an average test accuracy of 98.3%.

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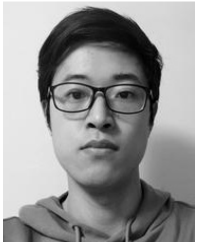
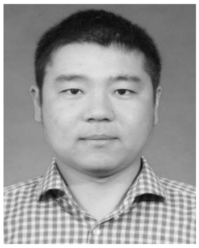


CHANGLU XU was born in Heze, Shandong, in 1995. He is currently pursuing the master's degree with Shanghai Dianji University. His current research interests include machine vision and pattern recognition.

LINSHENG LI was born in Hunan, in July 1975. He received the Ph.D. degree from the Department of Photo-Electronic Engineering, Chongqing University, in December 2011. In July 2000, he was engaged in mechanical design work at China National Nuclear Corporation 741 Mine. From 2005 to 2018, he was engaged in teaching and scientific research with the University of South China and served as the Head of the Department. Since 2019, he has been involving in teaching and scientific research with Shanghai Dianji University, and serving as the Director for the Graduate Management Office. He is currently an Associate Professor and a Master Supervisor with the Shanghai Institute of Electrical Engineering. His research interests include machine vision and robotics.

JIWEI LI was born in Suqian, Jiangsu, in 1997. He is currently pursuing the master's degree with Shanghai Dianji University. His current research interest includes machine vision.



CHUANBO WEN was born in Henan, in August 1981. He received the bachelor's degree in mathematics and the master's degree in applied mathematics from Henan University, in 2004 and 2007, respectively, and the Ph.D. degree in control theory and control engineering from Shanghai Jiao Tong University, in 2015.

From 2015 to 2016, he was a Senior Visiting Scholar with Brunel University London, U.K. He is currently a Professor and the Vice President of the School of Electrical Engineering, Shanghai Dianji University. His research interests include complex equipment fault diagnosis and life prediction, multi-source information fusion, and artificial intelligence. He is a member of the Information Fusion Special Committee of the Chinese Society of Aviation, the Fault Diagnosis and Safety Special Committee of the Technical Process of the Chinese Association of Automation, and the Shanghai Nuclear Power Hainan Service Base Cooperation Alliance. He is a Reviewer of several journals, including IEEE Transactions on Signal Processing, IEEE Transactions on Aerospace and Electronic Systems, *Neurocomputing*, *Science in China Series F: Information Sciences*, and *Acta Automatica Sinica*.