Ultrasonic C-scan image evaluation system for electric contacts with model and feature selection

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In this paper, in order to improve the traditional evaluation of electric contact, the novel ultrasonic C-scan image evaluation system is built by combining the Support Vector Machine (SVM), the Mutative Scale Chaos Optimization (MSCO) and the Genetic Algorithm (GA). The SVM is used as a classifier, the MSCO is employed as a model selector to optimize the parameters of SVM, and the GA is applied as a feature selector to get rid of redundant and irrelevant features for this system. In the experiment, the grayscale histograms are extracted as the feature dataset from the ultrasonic C-scan images. Then the novel system can classify the electric contacts into three categories with high efficiency and accuracy by using a certain feature samples when the 10-fold cross validation procedure is applied: qualified product, unqualified product and repairable product. Some comparisons have been made to show that the model selection and the feature selection are very important for improving the average evaluation accuracy rate.

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1. Introduction

Ultrasonic C-Scan is a nondestructive inspection technique for composites in which a short pulse of ultrasonic energy is incident on a sample. Measurement of the transmitted pulse indicates the sample's attenuation of the incident pulse. The attenuation of the pulse is influenced by voids, delaminations, state of resin cure, the fiber volume fraction, the condition of the fiber/matrix interface and any foreign inclusions present. Ultrasonic C-scan can produce comprehensive, high quality corrosion/erosion images.

Ultrasonic C-scan imaging technology is developed on the basis of the computer technology, information technology and image technology. It can provide much useful information about the defects. The extraction and the analysis of the defect information need the digital image processing technology to realize. Ultrasonic C-scan imaging technology is one of the most attractive modern ultrasonic nondestructive testing technologies, as well as one of the key technologies of realizing the defects locations and nondestructive evaluations. It has become a very active research direction in the field of ultrasonic nondestructive testing, which has been applied to the inspection of materials in many industry areas[1-6]. [1] introduced that ultrasonic techniques are being increasingly used for nondestructive testing and quality control of bonds between the electrical contacts and the support members of the contact assemblies. The delayed pulse echo and the through transmission are discussed with respect to their limitations and merits for the brazed bond quality between the silver- cadmium oxide or silver contact and the copper support. [2] proposed a low-cost, electro-mechanical ultrasonic scanner for obtaining high resolution C-scan images of the friction skin ridge structure found on the digits of the hands or feet in order to create imagery of sufficient quality for use in automated personal identification systems. The C-Scan ultrasonic imaging is applied to evaluate grouted post-tensioned tendons in [3]. A new intelligent instrument is proposed by [4], specialized in inspecting defects in rails. It is based on the ultrasonic nondestructive examination theory. Petculescu presented a nondestructive method to obtain and analyze ultrasound images of bone tissues by C-scan in [5]. By applying this method one can obtain bi-dimensional ultrasonic images in which the differences in the image contrast result from the ultrasound-bone tissue interaction. A practical ultrasonic C-scan techniques for NDT of laminated composite materials are developed and applied in [6], with an aim to trace specific artificial defects.

Ultrasonic C-scan imaging technology is an effective method for the electric contact brazing surface quality evaluation. Ultrasonic C-scan images can provide the quality characteristics of the electric contact brazing surface such as defects, locations, sizes and shapes. In order to evaluate the ultrasonic C-scan images, the digital image processing technology is applied to get brazing rate from the ultrasonic C-scan images about electric contact brazing surface. The traditional method to evaluate electric contact quality is to calculate the electric contact brazing rate. In some electrical contact manufactures in China, the JTUIS (Jiao Tong University Instrumental System) ultrasonic C-scan imaging nondestructive evaluation system has been used to evaluate the electric contact brazing surface quality, developed by Xi’an Jiaotong

University. Brazing rate can be calculated depending on size, grey and shape information for this system by the ultrasonic C-scan images and used for evaluating the electric contact brazing surface quality. Unfortunately, the grey and the shape information are difficult to achieve without high quality images by the JTUIS, then the calculations of brazing rate aren't reliable. Therefore, to achieve more satisfactory results, the professionals usually participate in the evaluation process. In the present methods, evaluations for ultrasonic C-scan images of electric contacts are based on JTUIS and professionals, thus, the efficiency is reduced.

The contribution of this paper is that the novel ultrasonic C-scan image evaluation system for electric contact converts the evaluation problem into classification problem by combining the characteristics of Support Vector Machine (SVM), Mutative Scale Chaos Optimization (MSCO) and Genetic Algorithm (GA) in order to improve the efficiency. Some comparisons are made to show that the novel evaluation system is more effective, and the model selection and the feature selection are important for improving the average evaluation accuracy rate.

2. Overview of the ultrasonic C-scan image evaluation system

In order to build the novel system with the best average evaluation accuracy rate by using fewer features, training SVM is the key to find out the best parameters and feature subset for SVM by the model selection and the feature selection.

Fig.1 illustrates the SVM training configuration. The samples of ultrasonic C-scan images are obtained by the JTUIS ultrasonic C-scan imaging nondestructive evaluation system. Features, next, are extracted by employing grayscale histograms of images from the samples library as the image features and normalized, then form the feature dataset of ultrasonic C-scan images. The model selection is realized by MSCO, and the feature selection is performed by GA, respectively. The SVM is applied as a classifier. When the SVM is trained, the outputs of SVM will guide the MSCO's model selection to find out the best SVM parameters and GA's feature selection to set up a good subset of features. At the end, the novel ultrasonic evaluation system will use the best parameters and fewer features to achieve the same or better classification. After the SVM training, the SVM will be tested by evaluating samples gotten from feature dataset.

2.1 Support vector machine (SVM) and model selection of SVM

● **SVM**

SVM is a new generation learning system based on recent advances in statistical learning theory, which is introduced by Vapnik[7]. SVM applies the concept of decision planes to define decision boundaries. A decision plane is one that separates between a set of objects with different class memberships. The basic idea of SVM to deal with the classification problem is to map the sample space to a high-dimensional feature space. Then find out the optimal hyperplane in the feature space, which actually corresponds to the original nonlinear hyperplane in the sample space. SVM can avoid the problem that should be directly dealt with in high dimension space through the features of kernel function.

Support a set D of n training examples $\left(\mathbf{X}_i, y_i\right)$ are given with binary outputs $y_i = \pm 1$ corresponding to the two classes. SVM can find the optimal hyperplane leaving the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from the hyperplane. This is equivalent to performing structural risk minimization to achieve good generalization. Assume that there are l examples from two classes

$$(\mathbf{X}_1, y_1), (\mathbf{X}_2, y_2), \cdots, (\mathbf{X}_l, y_l),\ \mathbf{X}_l \in R^N,\ y_i \in \{-1, +1\},\ l \in N \tag{1}$$

where $\mathbf{X}_i = \left[x_i(1), x_i(2), \cdots x_i(n)\right]^{\mathrm{T}}$. $\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_l$ are input variable vectors. y_i is the class label of $\mathbf{X}_i$.

According to the principle of structural risk, the minimum risk boundary of classification problem can be converted to the following optimization problem

$$\begin{aligned} &\min \quad \frac{1}{2}\|\boldsymbol{\omega}\|^2 + C\left(\sum_{i=1}^{N}\xi_i\right) \\ &s.t. \quad y_i[\boldsymbol{\omega}^{\mathrm{T}}\Phi(\mathbf{X}_i) + b] - 1 + \xi_i \ge 0, \quad i = 1,\ 2, \cdots, N. \end{aligned}$$

After applying Lagrange function and a series of optimization methods, the optimization problem will be transformed to find maximum of the following function[7]

$$\begin{aligned} &\max_{\alpha} \quad Q\left(\alpha, \Phi\left(x_i\right)\right) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \Phi^T(x_i)\Phi(x_j) \\ &s.t. \quad 0 \le \alpha_i \le C, \quad i = 1, 2, \cdots, N \\ &\qquad \sum_{i=1}^{N}\alpha_i y_i = 0. \end{aligned} \tag{2}$$

Corresponding to a quadratic programming problem, Equ.(2) has a unique solution under the restriction of the range. According to the functional theory, there is an inner product function $K(x_i, x_j)$ satisfying the Mercer condition, which is

$$K(x_i, x_j) = \Phi^T(x_i)\Phi(x_j),$$

$K(x_i, x_j)$ is the kernel function. α_i are the solutions to the following quadratic programming problem

$$\max_{\alpha} \quad Q\left(\alpha, \Phi\left(x_i\right)\right) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$s.t. \quad 0 \le \alpha_i \le C, \quad i = 1, 2, \cdots, N$$

$$\sum_{i=1}^{N} \alpha_i y_i = 0.$$

It can be proved that only a few α_i are not zero. The corresponding samples are support vectors.

Thus optimization decision function can be obtained as follows

$$f(x) = sign(\sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b),$$

where $sign$ is the symbol function, l is the number of support vectors, b is the classification threshold.

Choosing different kernel functions can realize different SVM algorithms. There are three main kernels[8].

(1) Polynomial kernel

$$K(\mathbf{X}, \mathbf{X}_i) = \left[(\mathbf{X} \cdot \mathbf{X}_i) + 1\right]^q$$

The SVM is a *q-th* order polynomial classifier.

(2) Gaussian kernel (RBF kernel)

$$K(\mathbf{X}, \mathbf{X}_i) = \exp(-\|\mathbf{X} - \mathbf{X}_i\|^2 / \gamma^2)$$

Gaussian kernel corresponds to a radial basis function (RBF) neural network. The SVM is a RBF classifier.

(3) Sigmoid kernel

$$K(\mathbf{X}, \mathbf{X}_i) = \tanh(v(\mathbf{X} \cdot \mathbf{X}_i) + C)$$

Sigmoid kernel corresponds to a two-layer sigmoid neural network.

Because the hyperparameters of Gaussian kernel are fewer than other kernels for SVM, it is easier to find out the better hyperparameters by Gaussian kernel than those by other kernels. Therefore, the Gaussian kernel will be used in this system. In the Equ.(1), the $\mathbf{X}_i$ denote the features vectors of the ultrasonic C-scan images, which are fed into the SVM, and the $y_i \in \{-1, 0, +1\}$ denote the three categories of electric contacts, which are the output of the SVM, when the SVM is used in the novel system. $y_i = -1$ denotes the unqualified electric contact, $y_i = 0$ denotes the repairable electric contact and $y_i = 1$ denotes the qualified electric contact.

- **Model selection of SVM**

For SVM classifier, the appropriate penalty parameter and kernel parameter must be chosen, referred to the model selection.

Because the Gaussian kernel is applied in SVM, the two parameters C and γ need to be chosen for a practical classification problem. Model selection, in fact, is an optimization problem. The optimization goal is to search optimal parameters C and γ so that SVM can accurately predict unknown data (test data). At present, several model selection methods have been proposed by some researchers. Such as, the grid search method[9], online gradient descent method [10], radial interval bounded method[11] and two lines searching algorithm[12]. Among them, the grid search method is more popular. However, the grid search almost searches each pair of (C, γ). (C, γ) that has the highest cross validation accuracy is the optimal parameter pair of SVM model. The grid search is similar to exhaustive search. So in some cases, the grid search is time-consuming and only gets the suboptimal results.

In order to avoid the shortcomings of the grid search method mentioned above, this paper applied the mutative scale chaos optimization to realize the model selection, which is practical, rapid and with highly accurate.

2.2 Mutative Scale Chaos Optimization (MSCO)

The chaos is a kind of universal phenomena in nonlinear systems. The chaos has three important dynamic properties: ergodicity, intrinsic quasi-stochastic property and the sensitivity depending on initial conditions. A chaotic variable can go non-repeatedly through each state in searching domain. These properties can be used to solve optimization problems. The method is called Chaos Optimization Algorithm (COA). COA can escape from local minima more easily than other stochastic optimization algorithms that escape from local minima by accepting some wrong solutions, such as simulated annealing and genetic algorithm[13].

The essences of the chaotic optimization algorithms are: (1) Maps derived by discretizing gradient models with Euler's method generate chaos if the dynamical systems are unstabilized by setting their sampling time larger. (2) Chaotic trajectories of the maps are useful to probe in wide ranges of the searching domain without being trapping into local optima. (3) The chaotic annealing method is available by gradually decreasing the sampling time of them. Until now, the most COAs have been proposed based on the second essence[14]. Bing Li applied the carrier wave method to add the chaotic variables to optimization variables and used the ergodicity property of chaotic variables to search[13]. Tong Zhang proposed the mutative scale chaos optimization (MSCO) method[15]. The searching space of optimizing variables was reduced continually and the searching precision was enhanced. Zicai Wang and MingJun Ji proposed the chaos simulated annealing (CSA) with replacing the Gaussian distribution by chaotic sequences in simulated annealing[16, 17]. Choi added the chaotic variables to the steepest descent searching algorithm and used the parallel search method to solve the optimization problem[18]. Zhou provided a general method for constructing a chaotic system based on the corresponding gradient descent system[19].

In this paper, the MSCO is applied for the optimization problem which has the global minimum

$$\begin{aligned} &\min \quad f\left(x_1, x_2, \cdots, x_n\right) \\ &s.t. \quad x_i \in \left[a_i, b_i\right],\ i=1,2,\cdots,n. \end{aligned} \tag{3}$$

The MSCO is described in detail as follows[15]:

Chaos variables are generated by $x_{k+1} = \mu \cdot x_k \left(1 - x_k\right)$ in the MSCO algorithm, where $\mu = 4$. The initial value of x_k is chosen between 0 and 1, but fixed points (0.25, 0.5 and 0.75) can't be chosen.

Step1: Set $k=0$, $r=0$, $x_i^k = x_i\left(0\right)$, $x_i^* = x_i\left(0\right)$, $a_i^r = a_i$, $b_i^r = b_i$ ($i = 1, 2, \cdots, n$). k is the iterative sign, r is the searching sign, $x_i\left(0\right)$ is the initial values, which are between 0 and 1, x_i^* is the optimal chaotic variables at this step. At the same time, the optimal result f^* is set as a very large number.

Step2: Map chaotic variables $x_i^k, i = 1, 2, \cdots, n$ into the variance range of the optimization variables by the following equation

$$mx_i^k = a_i^k + x_i^k \cdot \left(b_i^r - a_i^r\right).$$

Step3: If $f\left(mx_i^k\right) < f^*$, then $f^* = f\left(mx_i^k\right)$, $x_i^* = x_i^k$.

Step4: $k = k+1$, $x_i^k = 4x_i^k\left(1 - x_i^k\right)$

Step5: Repeat Step 2 to Step 4, until f^* becomes stable after certain iterations.

Step6: Reduce the searching space

$$a_i^{r+1} = mx_i^* - \lambda \cdot \left(b_i^r - a_i^r\right)$$

$$b_i^{r+1} = mx_i^* + \lambda \cdot \left(b_i^r - a_i^r\right),$$

where $\lambda \in \left[0, 0.5\right]$, $mx_i^* = a_i^* + x_i^* \cdot \left(b_i^r - a_i^r\right)$ is the better population. If $a_i^{r+1} < a_i^r$, then $a_i^{r+1} = a_i^r$; If $b_i^{r+1} < b_i^r$, then $b_i^{r+1} = b_i^r$. Then

$$x_i^* = \frac{mx_i^* - a_i^{r+1}}{b_i^{r+1} - a_i^{r+1}}.$$

Step7: Produce the new populations by $y_i^k = \left(1-\alpha\right)x_i^* + \alpha x_i^k$, where α is very small.

Step8: Repeat Step 2 to Step 4 by using y_i^k as chaotic variables.

Step9: Repeat Step 7 to Step 8, until f^* becomes stable after certain iterations k.

Step10: $r = r+1$. Reduce α and let $\alpha = \theta\alpha,\quad \theta < 1$. Then repeat Step 7 to Step 9.

Step11: If the stop criteria aren't satisfied, then repeat Step 10, or stop searching.

Step12: So far, mx_i^* is the optimal variable and f^* is the optimal result.

Although chaotic variables are ergodic, the chaotic variables will take longer time to find the optimal results when the space is very large. Thus, that gradually reducing the searching space of optimization variables is taken into consideration. At Step 6 and Step 7, the searching space of the mutative scale chaos optimization will be decreased.

Because the model selection is to search the two best parameters C and γ for SVM, the Equ.(3) converts to

$$\begin{aligned} &\min \quad f\left(C, \gamma\right) \\ &s.t. \quad C \in \left[0, 500\right], \gamma \in \left[0, 1\right]. \end{aligned}$$

The stop criteria for whole the system will be introduced in section 3.3.

2.3 Genetic algorithm (GA) for feature selection

In most practical cases, relevant features are not known as a priori. Often, a large number of features are extracted from ultrasonic signals to represent the flaws. Without adapting some kinds of feature-selection strategies, many of these features could be either redundant or even irrelevant to the flaw-classification task. Watanabe showed that it is possible to make two arbitrary patterns similar by encoding them with a sufficiently large number of redundant features[20]. Therefore, it is necessary to find out which features are used in a classification. This task is referred to feature selection. Feature selection is actually an optimization problem. This paper will apply binary encoding GA to solve the problem, which is described in detail as follows,

Step1: Initialize the parameters of the GA. Randomly generate initial population $pop\left(1\right)$, which is composed of *N* chromosomes by binary encoding method.

Step2: Calculate the fitness function $f\left(pop_i\left(t\right)\right)$ for each chromosome $pop_i\left(t\right)$ in population $pop(t)$. t means the iteration time.

Step3: If stop criteria are satisfied, GA stops. Or calculate the probability

$$P_i = f\left(pop_i(t)\right) / \sum_{j=1}^{N} f\left(pop_j(t)\right) \quad i = 1, 2, \cdots, N.$$

According to the probabilities P_i, select two parent chromosomes from $pop(t)$ to form new population $Newpop(t+1)$.

Step4: With a crossover probabilities P_c, cross over the $Newpop(t+1)$ to form $Crosspop(t+1)$.

Step5: With a small mutation probabilities P_m, mutate the $Crosspop(t+1)$ at each locus to form $Mutpop(t+1)$. Let $pop(t) = Mutpop(t+1)$ and return to Step2.

3. Experiments for ultrasonic C-scan image evaluation system for electric contacts

The flowchart of experiment for ultrasonic C-scan image evaluation system is shown in Fig.2.

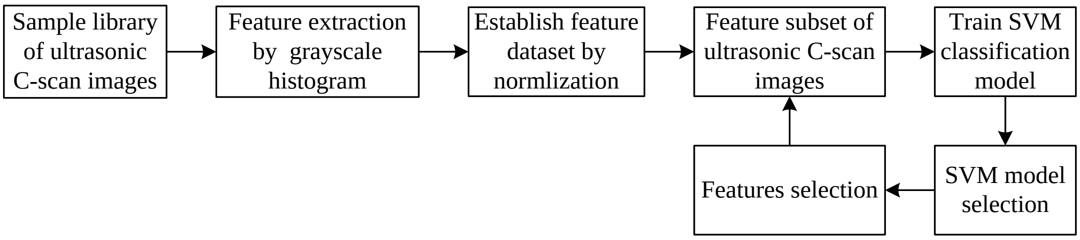


Fig.1: The SVM training of ultrasonic C-scan image evaluation system

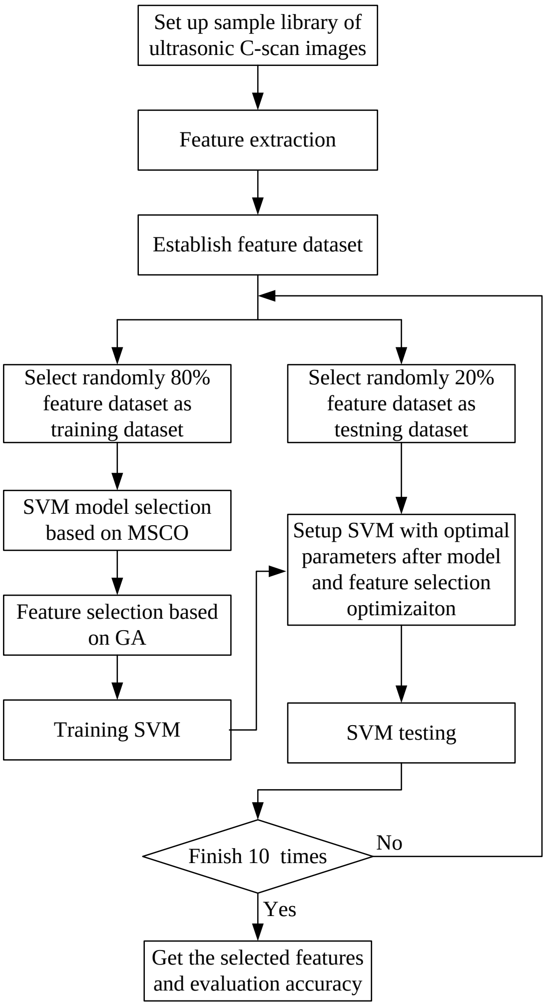


Fig.2: Flowchart for experiments

3.1 Sample library of ultrasonic C-scan images

The JTUIS ultrasonic C-scan imaging nondestructive evaluation system is shown in

Fig.3 developed by Xi'an Jiaotong University. In the novel ultrasonic C-scan image evaluation system, the JTUIS is used to collect the ultrasonic images.

The ultrasonic water-immersion focusing method has been used in JTUIS, which can intuitively reconstruct the position, shape and size of defects in the detected objects. Therefore, the ultrasonic water-immersion focusing method is suitable to evaluate the electric contact brazing surface quality. The water is couplant in the ultrasonic water-immersion focusing method. Ultrasonic Defectoscope (UD) generates ultrasonic waves and receives theirs echoes. The processor controls the UD and realizes the data acquisition and data store. The ultrasonic wave beams and the electric contact brazing surfaces keep vertical, and the progressive scanning is made for measured samples. Analog signals of ultrasonic echoes are transformed into digital signals and save them into the computer through the A/D card. Finally, the color ultrasonic C-Scan images are achieved.

To build ultrasonic C-scan image sample library, it is important that there are a huge amount of diversely representative samples. If the sample is too small or the samples haven't representativeness, the trained classifier has poor generation performance. In order to obtain enough representative samples, thousands of electric contacts are evaluated by the JTUIS and professionals in one electric contacts manufacture of Shanghai, and thousands of ultrasonic C-scan images are produced. With the help of experienced professionals in the factory, these images are divided into three categories of qualified electric contacts, unqualified electric contacts and repairable electric contacts. Fig.4 shows three types of ultrasonic C-scan grayscale images of the electric contact brazing surface. According to the grayscale images, if there is the grey in an image, the electric contact brazing surface is unqualified. If the image has no grey, but has little white, the electric contact brazing surface is qualified. If the image has no grey, but has a lot of white, the electric contact brazing surface is repairable.

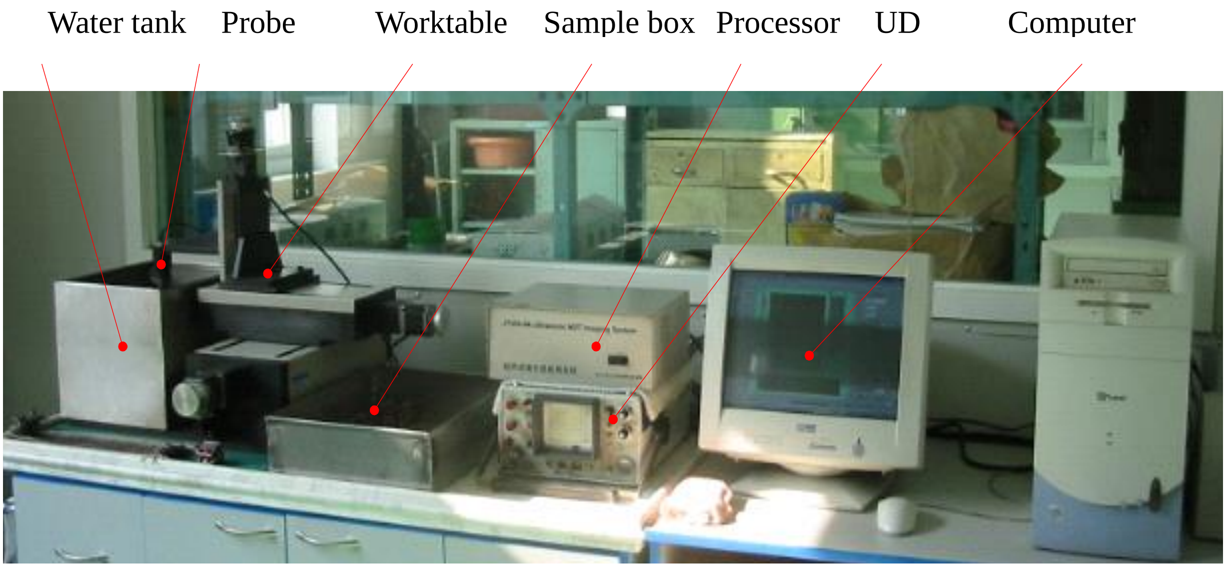


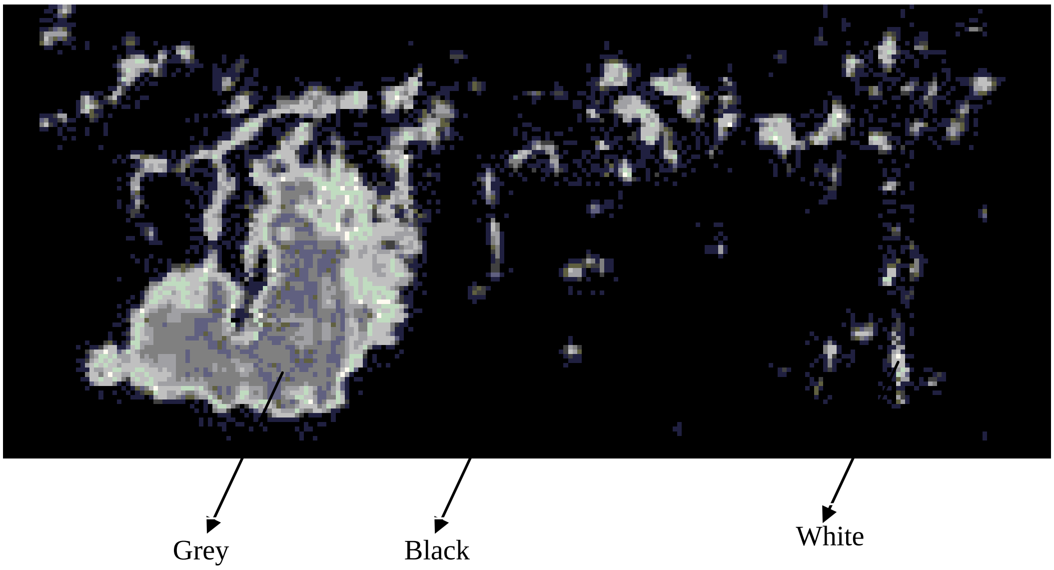
Fig.3: The JTUIS ultrasonic C-scan imaging nondestructive evaluation system

300 ultrasonic C-scan images are eventually selected (each category is 100) to establish the ultrasonic C-scan image samples library for electric contact brazing surface. Since the sizes of these 300 images are little different, they will be normalized to the same size by geometrical transformation before the features are extracted.

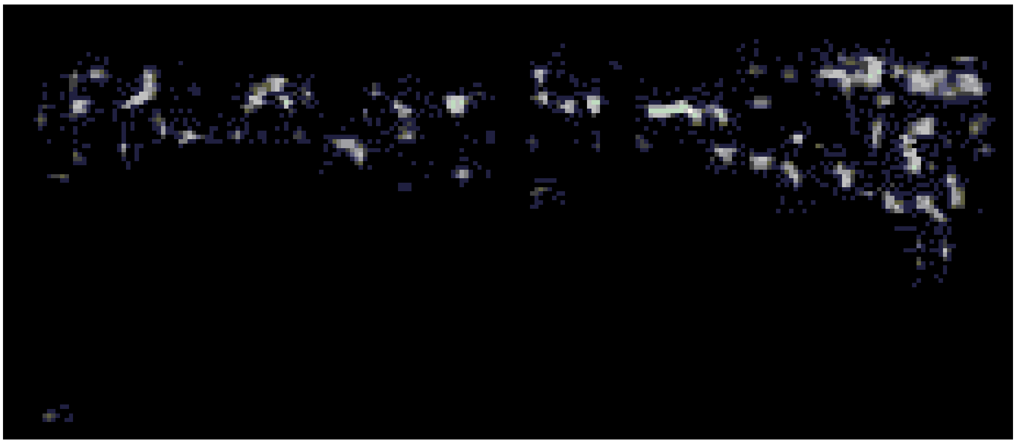
3.2 Feature extraction and feature dataset of ultrasonic C-scan images

In the color ultrasonic C-scan images, color information of the images is the main feature. Because the grayscale histogram is good at reflecting the color characteristics of the images, the novel evaluation system extracts the grayscale histograms of color ultrasonic C-scan images as the features. In order to achieve the grayscale histogram, the color ultrasonic C-scan images will be transformed to grayscale images. One grayscale image can be represented by 256 bins, after getting the grayscale histogram. One bin represents a feature.

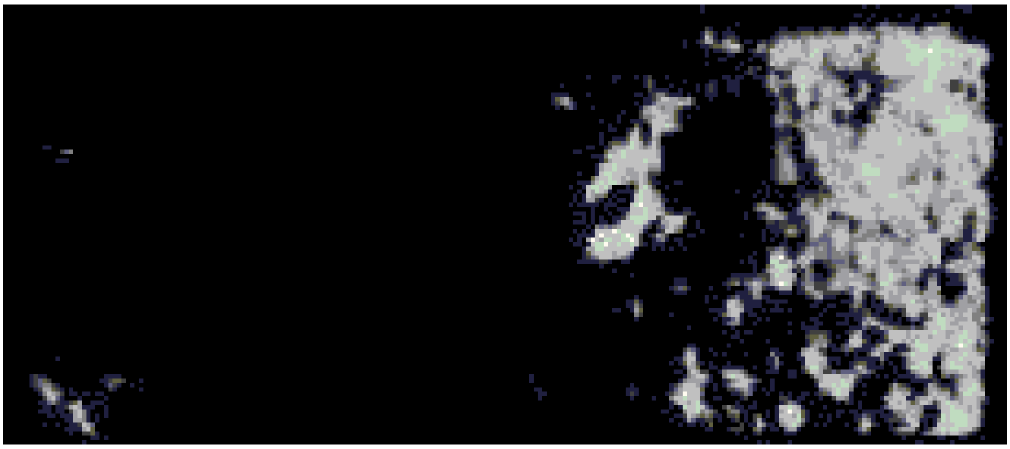
Therefore, one ultrasonic C-scan image gets 256 features, because grayscale histogram has 256 grayscale intensities. For instance, Fig.5 shows the grayscale histograms of all the ultrasonic C-scan images in the Fig.4. In Fig.5, three categories of ultrasonic C-scan images of the electric contact brazing surface have obviously different grey levels. The stronger the intensity of the darkest color and the weaker other colors are, the better the qualification is such as the case shown in Fig. 5 (b). Fig. 5 (a) shows an unqualified electric contactor greycolor figure eventhough the figure has a high intensity of the darkest color. However, the intensities of all other colors are also reaching a certain intensity level. Fig.5 (c) belongs to the repairable category since only a part of other colors reach a certain intensity level. Therefore, these three categories are easily classified.



(a) Unqualified electric contact brazing surface

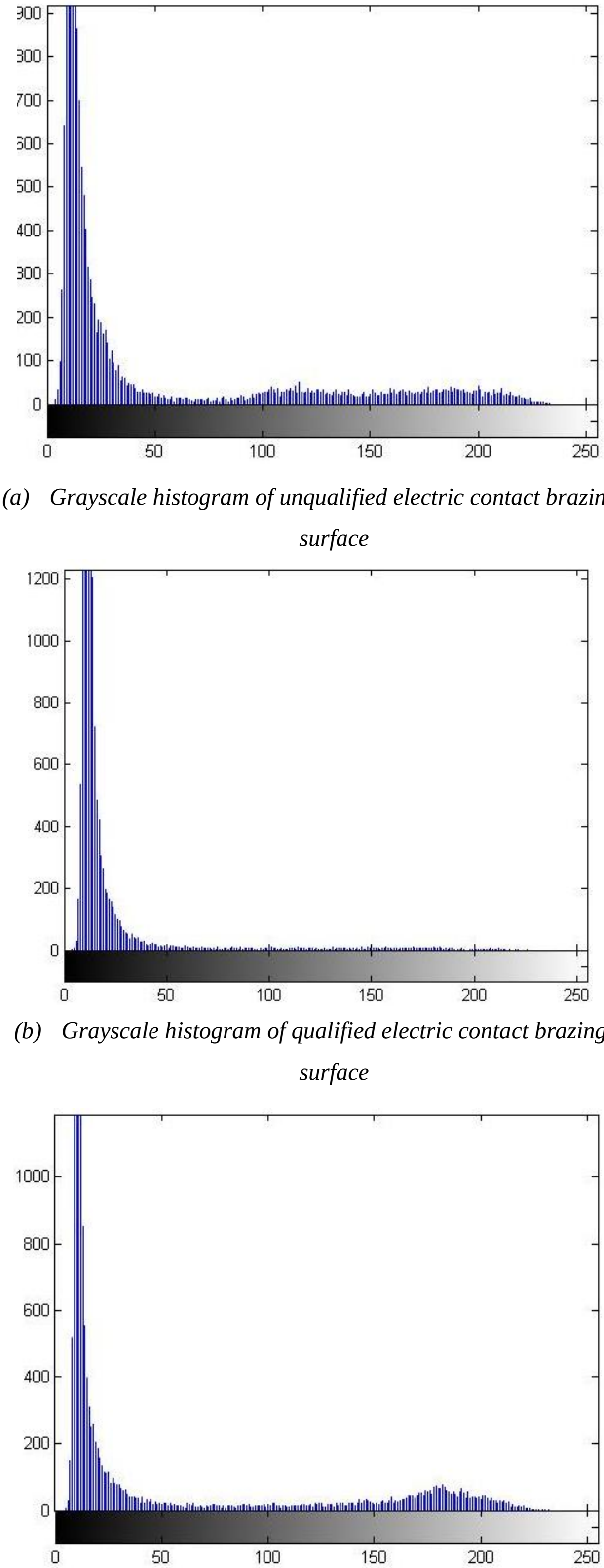


(b) Qualified electric contact brazing surface



(c) Repairable electric contact brazing surface

Fig.4: Three categories of ultrasonic C-scan grayscale images of the electric contact brazing surface



(a) Grayscale histogram of unqualified electric contact brazing surface

(b) Grayscale histogram of qualified electric contact brazing surface

(c) Grayscale histogram of repairable electric contact brazing surface

Fig.5: The grayscale histograms of three categories of ultrasonic C-scan images of the electric contact brazing surface

The feature dataset is established after each grayscale histogram is extracted from the ultrasonic C-scan image samples library. The feature dataset can be directly used in ultrasonic C-scan image evaluation system for electric contacts.

3.3 SVM model selection and feature selection

In this paper, the MSCO is applied to realize the model selection of SVM. The searching spaces of C and γ are $[0, 500]$ and $[0, 1]$, respectively. Other parameters for MSCO are set as $\lambda = 0.5,\ \theta = 3/4,\ k = 100$.

The GA is the feature selector. Because 256 features are gotten from the ultrasonic C-scan images, a simple binary encoding scheme is used for GA. Namely, the 256-bits binary is used as a chromosome to represent a subset of features. Each bit is a gene. Every gene of a chromosome represents a feature extracted from the ultrasonic C-scan image. Different chromosomes represent different subsets of features. If the *i*-th gene is 1, the *i*-th feature is selected; otherwise the feature is discarded. One population has *N* chromosomes. The *N* is set as 100 for the initial population. The initial population has 100 chromosomes. Every gene in the initial population is produced randomly. The parameters are set for the GA as $N = 100,\ P_c = 0.8,\ P_m = 0.05$. The goal of the feature selection is to use fewer features to make the SVM get the same or better performance. Therefore, the fitness function should have two terms: the classification accuracy and the number of selected features. Each fitness function contains a certain number of features. If two feature subsets achieve the same performance, while containing different number of features, the subset with fewer features is preferred. Accuracy is more concerned than the feature subset size for the feature selection. So one fitness function is used by combining the two terms as follows

$$f = 10^4 Accuracy + 0.5 Zeros, \qquad (4)$$

where *Accuracy* corresponds to the classification accuracy on a testing dataset for a particular subset of features, and *Zeros* corresponds to the number of features not selected (i.e., zeros in the chromosome). On the basis of the weights, the *Accuracy* term dominates the value of the fitness function. This result implies that individuals with higher accuracy will outweigh individuals with lower accuracy, no matter how many features they contain. According to Equ. (4), the value of the fitness function of each population is calculated in GA. Finally, the maximal fitness and the corresponding feature combination are treated as the current optimal solution and feature combination.

The stop criteria for the MSCO and the GA are the iteration number reaches the maximum number of iterations or the evaluation accuracy rate does not improve after 100 consecutive iterations. Therefore, the maximum number of iterations is 100.

4. Experimental results and analysis

The novel ultrasonic C-scan image evaluation system will take some time to train SVM and GA. After the training is finished, the system is set up and used to evaluate the electric contacts. The running time will be short and the real-time performance will be satisfied.

A number of experiments and comparisons have been performed by using the feature dataset shown in Table.1 to demonstrate the importance of the model selection and the feature selection. In each experiment, 10-fold cross validation procedure is applied. Then the final evaluation accuracy is determined by the average accuracy of ten-time experiments. The paper will show the experiment of the function with model selection when the evaluation system only has the model selector.

Table.1: Properties and distributions of the feature dataset

Category	The sample number	The feature number for each sample	Training dataset	Testing dataset
Qualified products	100	256	80	20
Unqualified products	100	256	80	20
Repairable products	100	256	80	20

The paper will show the function of model selection when the evaluation system with only model selector. So the ultrasonic C-scan image evaluation system with only model selector is first set up to evaluate the electric contacts. The grid searching and MSCO are applied as model selectors in this system. Because the system has no specific feature selection, the full features have been used.

The system with the MSCO model selector achieves 92.5% average evaluation accuracy rate, while the system with the grid searching model selector just reaches 87.5% accuracy rate. When the present method is used to evaluate the electric contacts, 87% average evaluation accuracy rate is obtained. Because the SVM has not been used, the C and γ do not exist. Therefore, the evaluation system with only model selection is better than the present methods, and the MSCO model selector outperforms the grid searching model selector. The system with MSCO model selector has a great improvement in terms of the average evaluation accuracy rate.

In addition, the feature selector has been added into the evaluation system only with the model selector in order to eliminate redundant and irrelevant features. The evaluation system with the model and feature selection improves the average evaluation accuracy rate from 92.5% to 96.7% and reduces the feature number from 256 to 130. It is shown that the performance of the SVM classifier can be improved to a certain level. However, the GA can get rid of 126 features and reach a higher average evaluation accuracy rate. Because of elimination of redundant and irrelevant features, the training time and testing time will be reduced, and the generalization of the evaluation system is improved. The experimental results and comparisons are shown in Table.2.

Table.2: The experimental results and comparisons

Ultrasonic C-scan Evaluation system	The parameters of SVM		Number of selected features	Average evaluation accuracy rate
	C	γ		
Present evaluation system	Non	Non	256	87%
Model selection of grid search	32	7.81×10^{-3}	256	87.5%
Model selection of MSCO	291.23	6.29×10^{-9}	256	92.5%
Model selection of MSCO and feature selection of GA	23.75	4.68×10^{-8}	130	96.7%

From experiments, the novel system has demonstrated the effectiveness for evaluating the quality of electric contacts. The model selection can find the better parameters and make the classifier in the better condition, which can improve the classification accuracy of the model selector. The feature selection can also reduce the number of relevant features and improve the system running speed and evaluation accuracy rate. Therefore, the model selection and the feature selection are very important for ultrasonic C-scan image evaluation system.

5. Conclusions

This paper employs SVM, MSCO and GA to build up a novel ultrasonic C-scan image evaluation system with model and feature selection for electric contacts. The system uses the MSCO and the GA as the model selector and the feature selector, while the SVM is used as a classifier. At the beginning of the experiments, the model selection is added into the ultrasonic C-scan image evaluation system to show that the model selection can improve the average evaluation accuracy rate. At the meantime, it is shown that the MSCO model selector is better than the grid searching model selector, when they are applied in the novel system, respectively. Furthermore, the model selector and the feature selector are both added into the ultrasonic C-scan image evaluation system to show that the model selector will further improve the average evaluation accuracy rate. At the end, the analysis results show that the ultrasonic C-scan image evaluation system with the model and feature selection provides the better performance for improving average evaluation accuracy rate.

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