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A vision inspection system for the surface defects of strongly reflected metal based on multi-class SVM

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ABSTRACT

This paper describes the designing and testing process of a vision system for strongly reflected metal's surface defects detection. In the authors' view, an automatic inspection system has the following stages: image acquisition, image pre-processing, feature extraction and classification. Thus, the system including four subsystems is designed, and image processing method and pattern recognition algorithm that perform specific functions are outlined. First, the study uses wavelet smoothing method to eliminate noise from the images. Then, the images are segmented by Otsu threshold. At last, five characteristics based on spectral measure of the binary images are collected and input into a support vector machine (SVM). Furthermore, kernel function selection and parameters settings which are used for SVM method are evaluated and discussed. Also, a very difficult detection case for the surface defects of strongly reflected metal is depicted in details. The classification results demonstrate that the proposed method can identify seven classes of metal surface defects effectively, and the results are summarized and interpreted.

1. Introduction

Generally, strongly reflected metals include aluminum, gold, copper and silver, etc. Currently, those metals have been widely used in different areas, and become the dispensable raw materials in several industries such as power electronics, automobile industries, shipping, domestic electronics, communications and construction industries, etc. Obviously, the surface quality of those metals will directly influence the capability and quality of the final products. However, defect inspection of strongly reflected metal is a simply repetitive and highly concentrated work. For traditional methods such as artificial visual detection and frequency flashlight detection, due to the disadvantages of their low random inspection rate, bad real-time capability, low inspection confidence and bad inspection environment, they could not meet the industrial requirements properly. As a result, the developments of on-line vision-based systems which are capable of performing inspection tasks have been promoted. Enhanced quality measurement helps to improve the performance of the system as follows:

1. Improve controlling of the process, e.g. faster reaction of processing faults, avoidance of disaster events, etc.
2. Improve overall process efficiency, e.g. avoidance of downstream processing of faulty material, optimizing downstream processing (repair, downgrading, and upgrading).
3. Improve customer relationships, e.g. reducing the claims delivering documented quality.

Most of the presently applied inspection systems perform defect detection. However, defect classification still remains a research subject. The strongly reflected metal is the one who can be described as the most difficult classifying metal in defects classification. Most metal surface defects are tiny involving obvious faulty items such as holes, stains, scratches, pilling, indentation, burrs and other ill-defined defects. These defects are small in size, refractive in light and can not be described using explicit measures, which make automatic defect detection difficult.

The research issues in defect inspection are widely open. In early days, with the absence of appropriate algorithms, the researches mostly focus on hardware design, especially in sensory system. And most frequently, sensory systems use CCD chips (Pernkopf & O'Leary, 2003; Zhang et al., 2008). However, alternative strategies, including laser scanning (Abuazza, Brabazon, & El-Baradie, 2003, 2004), ultrasound (Kercel, Kisner, Klein, Bacher, & Pouet, 1999), and X-ray image sensor systems (Boerner & Strecker, 1988; Mery & Filbert, 2002; Naso & Pantaleo, 2005) are gaining ground.

In recent years, developments in image processing, computer vision, artificial intelligence and other related fields have

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significantly improved the capability of visual inspection techniques. Up to now, several kinds of inspection systems have been proposed and have completely used image processing technologies and pattern recognition technologies. Piironen, Silven, Pietikainen, and Laitinen (1989, 1990) described a prototype for an automated visual on-line metal strip inspection system which is based on morphological preprocessing and combined statistical and structural defect recognition. The computational requirements for this system are large. Frayman, Zheng, and Nahavandi (2006) developed a machine vision system for automatic inspection of surface defects in aluminum die casting. The system used a hybrid image processing algorithm based on mathematic morphology to detect defects with different sizes and shapes. The feed-forward neural network technique has been used to detect defects of cold rolled strips (Kang & Liu, 2005), but FFN has some problems, e.g. easily getting into local minimum and long learning time, etc. Also the feature vectors used in this paper are simple and are non sensitive to distinguish diverse defects. Liang, Ding, Zhang, and Chen (2008) proposed a surface defect detection algorithm of copper strips based on RBF network and support vector machine that can detect all kinds of defects efficiently in real-time environment, and used Pseudo Zernike moments as the feature vectors. Similarity-based algorithms as well as texture algorithms have been developed for aluminum casting (Fernandez, Platero, Campoy, & Aracil, 1993). Jia, Murphey, Shi, and Chang (2004) described a real-time visual inspection system that used support vector machine to automatically learn complicated defect patterns of hot rolled steel. In order to achieve efficient computed results, the authors used rough filtering, and defect candidate finding to extract features. Experimental results demonstrate the potential of a support vector machine as a promising classifier for defect (seam) data with application in real-time manufacturing environment. However, this system has some limitations, e.g. it aims at detecting some special defect "seams", and the accuracy is not satisfied. Wang, Zhang, Mu, and Wang (2008) proposed an inspection system which adopted a self-adaptive weight averaging filtering method to preprocess image, and used the moment invariants to pick up the characters of typical defects. Furthermore, the eigenvectors were identified by the RBF neural networks. However, as the input space is in high dimension, the RBF network requires a prohibitively large number of Gaussian basis functions to cover a large number of inputs. Zheng, Kong, and Nahavandi (2002) used GAs for generating morphology processing parameters. This approach has the feasibility for the detection of structural defects and high detection accuracy for defects such as holes and cracks. However, due to the complexity of structural defects, the training sets selected manually sometimes do not reflect the common features of structural defects.

Feature extraction is a key step for the classification, and all the aforementioned references focus on gray value based feature extraction. Actually, metal surface defects are mostly similar to texture patterns. Numerous methods have been proposed to extract textural features either directly from spatial domain or from the spectral domain. Latif-Amet, Ertuzun, and Ercil (1999) used co-occurrence matrices based on wavelet sub-image characteristics to detect defects of textile fabrics. Co-occurrence matrices method is one of statistic methods in the spatial domain. Techniques in the spectral domain extract textural features by conducting frequency transforms such as Fourier transform (Tsai & Huang, 2003), Gabor transform (Tsa & Wu, 2000), or wavelet transform (Lee, Choi, Choi, Kim, & Choi, 1996; Lee, Choi, Choi, & Choi, 1997). Fourier transform is a global method, which just depicts the spatial-frequency distribution without regarding to the spatial domain information. Gabor is non-orthogonal and redundancy exists in different feature components, which results in computationally intensive in analyzing texture image. Wavelet based method is computationally intensive.

From Bayes classifiers to neural networks (Li, 2009; Liu, 2003; Pernkopf, 2004), there are many possible choices for an appropriate classifier. Among these, SVM would appear to be a good candidate for a high generalization performance without the need to add a priori knowledge, even when the dimension of the input space is very high (Chapelle, Haffner, & Vapnik, 1999).

This paper concentrates on research issues related to defect classification in strongly reflected metal and discussed the general methodology as well as specific examples of the algorithms. Furthermore, a case of copper strip surface defects classification using SVM is described.

The paper is organized as follows: the requirements for strongly reflected metal inspection systems and the proposed inspection system are described in Section 2, while the specific defect characterization and classification algorithms are detailed in Section 3. Section 4 showed the experimental results and discussed the performance of these algorithms. In Section 5, the authors summarized the results.

2. Inspection system analysis and design

2.1. Issues in metal defects inspection

At present, there are commercially available systems that can perform surface defect detection in strongly reflected metal at a high cost. However, the problem of defect classification, i.e. location of the defect region, prediction of the defect feature, and the optimal classifier are still open research issues. Inspection within metallic surfaces is conditioned by:

1. Usually, metal surface has a high reflection coefficient that makes it difficult to design a proper lighting system for defect enhancing.
2. The metal surface moves fast under the inspection devices and results in extremely high data volume: a typical metal is 1–2 m wide and moves with speeds ranging from 2–3 m/s. Consequently, data volume for 100% inspection is tremendous.
3. Diversity: there are a great variety of defect types and a single class of defects can be different in appearance such as size or orientation. Small changes in the production process can result in entirely new classes of defects. Furthermore, there are some "false defects" such as oil spots.

2.2. System design

A typical machine vision system will consist of several among the following components:

1. One or more digital or analog cameras with suitable optics for acquiring images.
2. Camera interface for digitizing images.
3. A processor (often a PC or embedded processor, such as a DSP).
4. A smart camera which combined all of the above.
5. Input/Output hardware (e.g. digital I/O) or communication links (e.g. network connection or RS-232) to report results.
6. Lenses to focus the desired field of view onto the image sensor.
7. Light sources.
8. A software to process images and detect relevant features.
9. A synchronizing sensor for part detection (often an optical or magnetic sensor) to trigger image acquisition and processing.
10. Some form of actuators used to sort or reject defective parts.

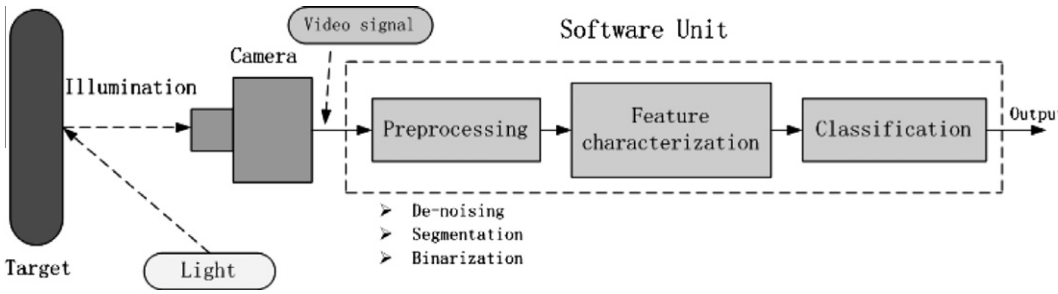


Fig. 1. Framework of inspection system.

In this paper, the authors consider a development environment consisting of four subsystems: image acquisition, image processing, feature extraction and defect classification. Fig. 1 shows the major stages of the surface defect detection system designed in this study.

First, the image is captured by the frame grabber which converts the output of the camera to digital format and places the image in computer memory. So it may be processed by the machine vision software. Next, the image processing software will typically take several steps to process an image. Often the image is first manipulated to reduce noise and to convert to a binary image. Feature extraction is used to obtain a feature discriminatory. Then, features obtained are input pattern to support vector machine (SVM), and SVM is employed for the metal defect classification task. As a final step, the software passes or fails the part according to programmed criteria. If a part fails, the software may inform a mechanical device to reject the part. Alternately, the system may stop the production line and warn a human worker to fix the problem that caused the failure.

2.2.1. Image acquisition subsystem

Image acquisition subsystem can serve as tools to improve manufacturing processes, as well as quality control in industries. Image acquisition hardware includes four parts: illumination, lenses, cameras, and camera-computer interfaces. Illumination is a particularly important component of the image acquisition system, which makes the essential features of an object visible. Lenses produce a sharp image on the sensor. The sensor converts the image into an analog or digital video signal. Finally, camera-computer interfaces accept the video signal and convert it into an image in the computer's memory.

The goal of illumination in machine vision is to make the important features of the object visible and reduce undesired features of the object. In order to do so, we have to consider how the light interacts with the object. One important aspect is the spectral component of the light and the object. To enhance the visibility of certain features, we can use the following issues, such as the composition of light, the directional properties of the illumination. Often, screens are used to prevent ambient light from falling onto the object and thereby lowering the image quality.

A light-emitting diode (LED) is a semiconductor device that produces narrow-spectrum light through electroluminescence. LED has many advantages: longevity, little power, produces little heat; furthermore, they can be used as flashes with fast reaction times and almost no aging. Since LEDs have so many practical advantages, they are currently the primary illumination technology used in machine vision application.

Reflection at metal causes light to become partially polarized. To suppress this light, the authors mount a polarizing filer in front of the camera and turn it in such a way that the polarized light is suppressed.

When taking all the above into consideration, the object of this paper: strongly reflected metal, are usually illuminated with a diffuse bright-filed back light illumination, as shown in Fig. 2.

The camera's purpose is to create an image from the light focused in the image plane by the lens. The most important component of the camera is a digital sensor. The two main sensor technologies are CCD (charge-coupled device) and CMOS (complementary metal-oxide–semiconductor). They differ primarily in their readout architecture, i.e., in the manner in which the image is read out from the chip. The CCD sensor consists of a line of light-sensitive photo detectors; typically, they are photo gates or photodiodes. CMOS sensor typically uses photodiodes for photo detection. In contrast to CCD cameras, the charge of the photodiodes is not transported sequentially to a readout register. Instead, each row of the CMOS sensor can be selected directly for readout through the row and column select circuits. Neither technology has a clear advantage in image quality. CMOS can potentially be implemented with fewer components, use less power and/or provide faster readout than CCDs. CCD is a more mature technology and is in most respects the equal of CMOS.

2.2.2. Preprocessing subsystem

Smoothing is often used to reduce noise within an image or to produce a less pixelated image. In production environment, the performance of the inspection system is seriously influenced by some noise e.g. camera thermal noise, digitizing noise, etc. To get the better performance in posterior stage, a good denoising processing of the image is necessary. In recent years, as the wavelet technology has been rapidly developed, wavelet has been successful in smoothing applications (Gonzalez & Woods, 2002). The computation of wavelet smoothing is based on multi-level 2D discrete wavelet transform. The detail coefficients are altered after the decomposition, and then used to reconstruct the real signal with the approximation coefficients. In wavelet smoothing, some detail

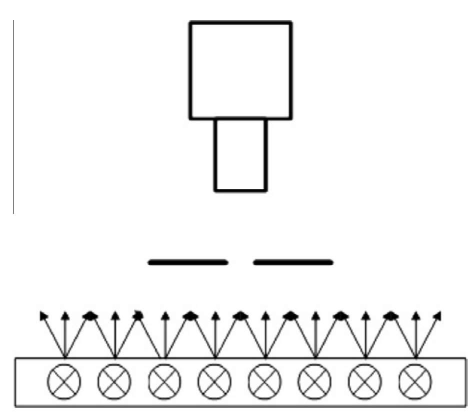


Fig. 2. Diffuse bright-field back light illumination.

coefficients are set to zero if their indexes are greater than a certain number. By changing the level for decomposition and the wavelet type, we can obtain the optimal combination for best appearance.

Segmentation is an important part of any automated image recognition system. The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

Image thresholding is crucial to the application of image segmentation. So it's necessary to find an optimal overall threshold that can be used to convert the gray scale image into a binary image, which separates an object's pixels from the background pixels. Thus, the authors used Otsu's method (Otsu, 1979), a threshold selection method from gray-level histograms, which chooses the threshold to minimize the intraclass variance of the threshold black and white pixels.

2.2.3. Characterization subsystem

In this subsystem, a set of known features that characterize defects are computed. The objective is to achieve a better classification by using as few as possible features to represent the defects. The most difficult problem is the defects of the same class are varying in different position, size, and orientation. So an available formation of feature vectors should make the defects with the same class invariant to expected transformation, i.e. translation, size, and rotation. Examples of such features include size, shape characteristics, as well as texture measurements on regions. Such features can be computed and analyzed by statistical or other computing techniques. On the other hand, sometimes the more complete feature vectors we apply, the better the classification results we could get. However, due to the curse of dimensionality, the feature set should be large enough to accurately predict the output as well as not be too huge. The set of computed features forms the input vectors to support vector machine.

2.2.4. Classification subsystem

A classifier can predict a class label of the input object. Actually, classifier performance depends greatly on the characteristics of the data to be classified. Typically, any trainable classifier uses a reference set of manually classified samples. These samples are referred as the training sets. The quality of the results for such a classifier depends mainly on two factors: the quality of the aforementioned feature set and the quality of the training set. The more complete the training set we use, the better the classification results we obtain for new samples. As a classifier model has been selected, the engineer then runs the learning algorithm on the gathered training set. Parameters of the learning algorithm may be adjusted by optimizing performance on a subset of the training set. As the optimal parameters have been obtained, the performance of the algorithm may be measured on a testing set which is separated from the training set.

3. Methodology

3.1. Wavelet transform for defect detection

The main advantages of wavelet are that they have a varying window size, which can be wide for slow frequencies and narrow for the fast ones, thus leading to an optimal time–frequency resolution in all frequency ranges. Furthermore, owing to the fact that windows are adapted to the transients of each scale, wavelets lack of the requirement of stationary.

As using the wavelet in image area, image is decomposed i.e., divided into four sun-bands and sub-sampled by applying DWT as shown in Fig. 3(a). These sub-bands are named as L-H1, H-L1, and H-H1 that represent the finest scale wavelet coefficients of detail images as well as sub-band L-L1 corresponds to low frequency level coefficients of approximation image. The sub-band L-L1 alone is further decomposed to obtain the next coarse level of discrete wavelet coefficients.

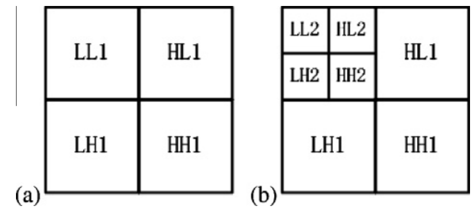


Fig. 3. Image decomposition (a) one level and (b) two levels.

For a two-level DWT decomposition as shown in Fig. 3(b). L-L2 will be used to obtain further decomposition. This decomposition process continues until final scale is reached. Coefficients obtained from DWT of approximation and detail images (sub-band images) are the basic features that are shown here as the useful characters for the texture classification. Micro-textures and macro-textures are statistically characterized by using the features in approximation and detail of DWT. Namely, the values of the L-L, H-L, L-H, and H-H sub-band images or combinations of these sub-bands or the obtained features from these sub-bands characterize a texture images very well.

3.2. Feature extraction

An important method for region description is to quantify its texture content. Two kinds of methods used for computing texture are statistical approach and spectral measure (Gonzalez & Woods, 2002). In this paper, we used spectral measure approach which based on Fourier spectral to compute texture. Detection and interpretation of the spectral features are simplified by expressing the spectrum in polar coordinates to yield a function $S(r,\theta)$, where S is the spectrum function while frequency r and direction θ are the variables in this coordinate system. For each frequency r, $S(r,\theta)$ is considered as 1-D function $S_\theta(r)$, Analyzing $S_\theta(r)$ for a fixed value of θ yields the behavior of the spectrum along a radial direction from origin. Analyzing $S_r(\theta)$ for a fixed value of r yields the behavior along a circle centered at the origin. By summing these functions, a global description is obtained:

$$S(r) = \sum_{\theta=0}^{\pi} S_\theta(r) \tag{1}$$

$$S(\theta) = \sum_{r=0}^{R_0} S_r(\theta) \tag{2}$$

$S(r)$ and $S(\theta)$ constitute a spectral-energy description for an entire image or region under consideration. We use some descriptors of the function $S(\theta)$ to characterize their behavior, including, the maximum value, the minimum value, mean, standard deviation, and distance between maximum value and mean. That is, totally 5 characteristics of $S(\theta)$ are obtained.

3.3. Support vector machine classifier

SVM have recently been proposed as popular tools for classification problem (Cristianini & Shawe-Taylor, 2000). For linearly separable problem, the main goal is to define a hyperplane which divides sample set so that all points with the same label are on the same side of the hyperplane while maximizing the distance between the two classes, through training the known sample set.

For linearly non-separable problem, the input data would be mapped into a high-dimensional feature space, and then the optimal separating hyperplane is constructed in the feature space.

3.3.1. Optimal separating hyperplane

Let $|(x_i, y_i)|_{i=1,\dots,N}$ be a training example set, each example $x \in R^d$ belongs to a class labeled by $y \in |+1, -1|$. If linear decision function exists in d-dimensional space:

$$g(x) = \omega^T x + b \tag{3}$$

where, x is the input vector, ω is the adjustable weight vector, and b is the bias, which makes $\omega^T x_i + b \geqslant 0$ corresponding to $y_i = +1$, $\omega^T x_i + b \leqslant 0$ corresponding to $y_i = -1$.

Accordingly, we can know that the sample set is linearly separable. The pair (ω, b) defines a separating hyperplane

$$g(x) = \omega^T x + b = 0 \tag{4}$$

The hyperplane makes the distance maximal. Hence, the optimal separating problem is equivalent to the following constraint optimization problem:

$$\min \quad \phi(\omega) = \frac{1}{2}\|\omega\|^2 = \frac{1}{2}\omega^T\omega \tag{5}$$

$$y_i[\omega^T x_i + b] - 1 \geqslant 0, \quad i = 1, 2, \dots, N \tag{6}$$

By means of the classical method of Lagrange multipliers, if we denote $\alpha_i \geqslant 0$, $i = 1, \dots, N$ with the N nonnegative Lagrange multipliers associated constraint (6), the problem of finding optimal separating hyperplane is equivalent to the maximization of the function

$$Q(\alpha) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j x_i x_j \tag{7}$$

Constraint to $\sum_{i=1}^{N}\alpha_i y_i = 0,\ \alpha_i \geqslant 0,\ i = 1, 2, \dots, N.$

The corresponding training examples (x_i, y_i) with nonzero coefficients α_i are called support vectors. The optimal decision function of classifying the above sample point can be written as:

$$g(x) = sgn\left[\sum_{i=1}^{m}\alpha_i^* y_i (x_i \cdot x) + b^*\right] \tag{8}$$

3.3.2. Linearly non-separable case

If the set S is not linearly separable, we must introduce N nonnegative variables such that

$$y_i[\omega^T x_i + b] - 1 + \xi_i \geqslant 0, \quad i = 1, 2, \dots, N \tag{9}$$

$\xi_i \geqslant 0$, $i = 1, 2, \dots, N$ are called slack variables.

The generalized optimal separating hyperplane is then regarded as the solution of the following minimizing problem:

$$\min \phi(\omega) = \frac{1}{2}\|\omega\|^2 + C\left[\sum_{i=1}^{N}\xi_i\right] \tag{10}$$

There into, C is a regularization parameter.

3.3.3. Nonlinear support vector machines

For the training example set that the authors want to classify is usually linearly non-separable, so the input data would be mapped into a high-dimensional feature space, and then the optimal separating hyperplane is constructed.

If we replace x by its mapping in the feature space $\Phi(x)$, Eq. (7) becomes

$$Q(\alpha) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \Phi(x_i)\Phi(x_j) \tag{11}$$

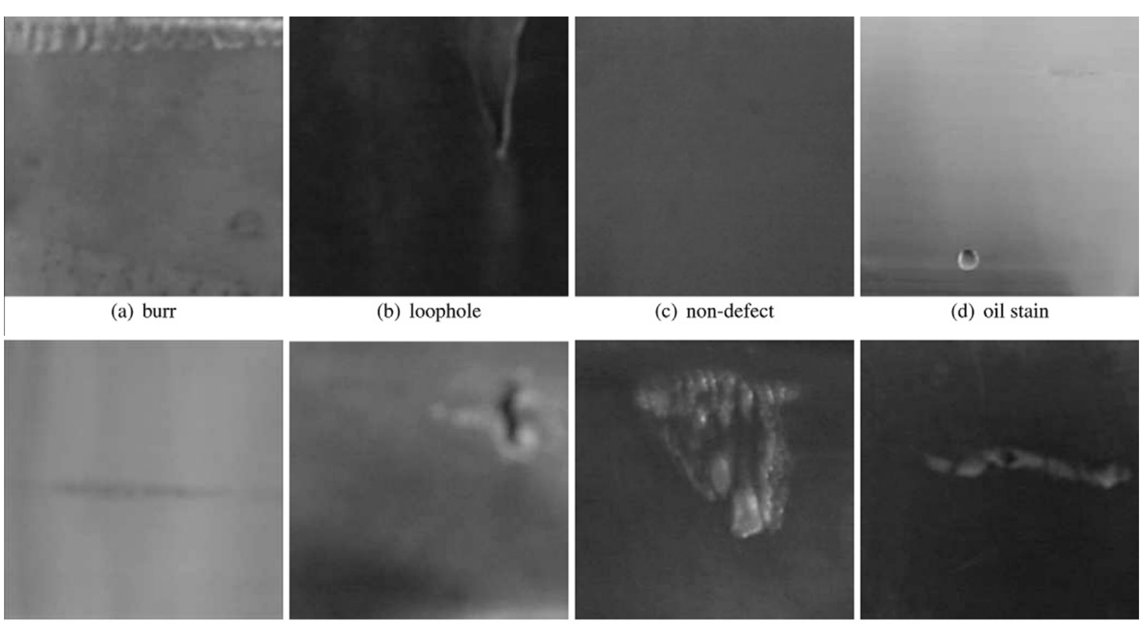
If we have $K(x_i, x_j) = \Phi(x_i)\Phi(x_j)$, then only K is needed in the training algorithm, and the mapping Φ is never explicitly used.

Once a kernel K satisfying Mercer's condition has been chosen, the training algorithm consist of minimizing

$$Q(\alpha) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \tag{12}$$

And the decision function becomes

$$g(x) = sgn\left[\sum_{i=1}^{m}\alpha_i^* y_i K(x_i \cdot x) + b^*\right] \tag{13}$$



(a) burr (b) loophole (c) non-defect (d) oil stain

(e) peeling (f) perforation (g) pit (h) scratch

Fig. 4. Original defect images.

4. Experimental results and discussion

In this section, the authors present the experimental results followed the previous approaches on copper strips to evaluate the performance of the proposed defect detection and classification method. All experiments are implemented on a personal computer, and images are 256×256 pixels with 8-bit gray levels. The approach is divided into three steps: (1) preprocessing; (2) feature extraction and (3) SVM classification.

4.1. Preprocessing

The main objective of preprocessing is to perform the image processing operation on the source image to enhance and smooth images, or remove 'noise' from an image. Among the collected samples, there are 7 major classes of defects on the copper strip surface that include burr, loophole, oil stain, peeling, perforation, pit, and scratch. The preprocessing includes the following four steps:

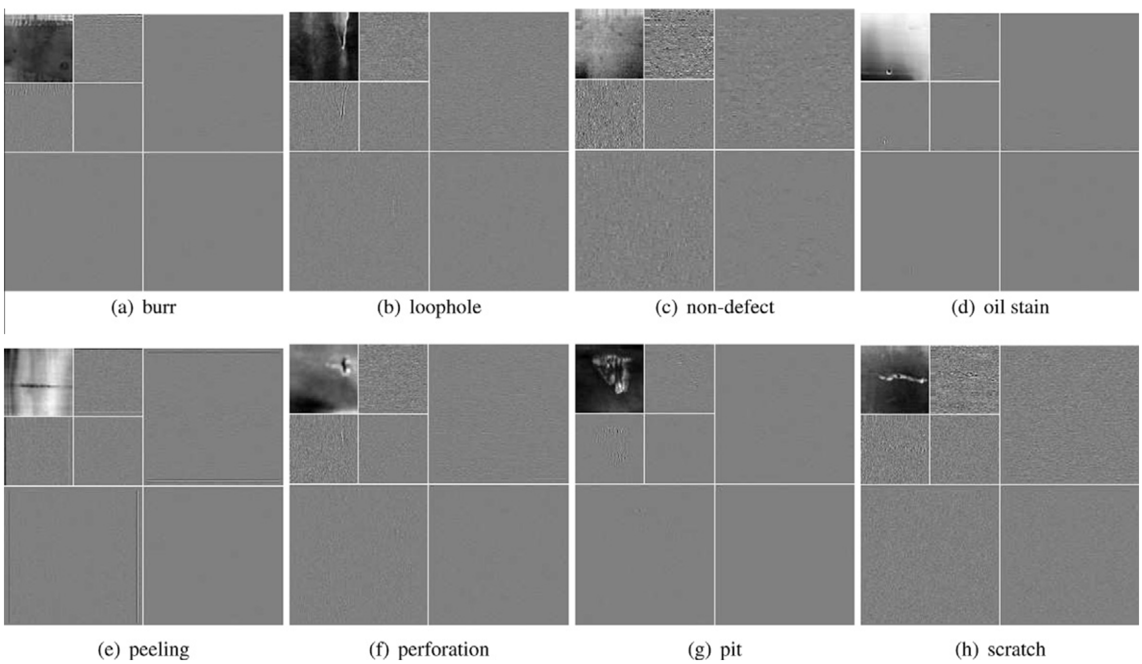


Fig. 5. Wavelet decomposition results.

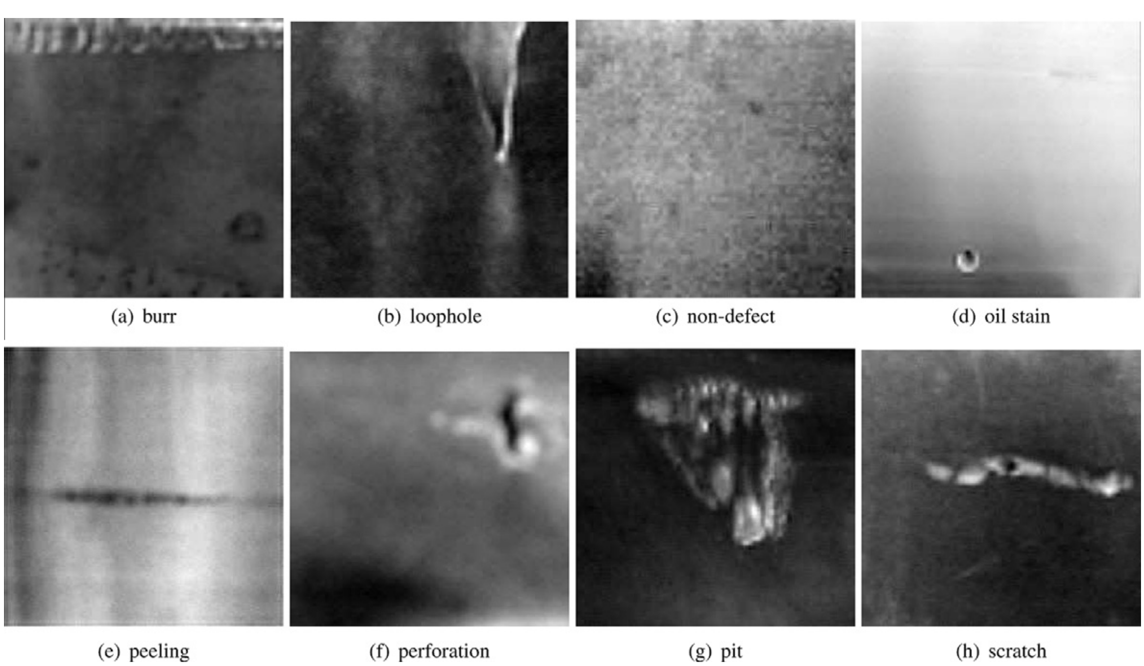


Fig. 6. Wavelet smoothing results.

Step1: wavelet decomposition
Step2: wavelet smoothing
Step3: Sobel filter
Step4: binary thresholding
The original images and the processed images are shown in Figs. 4–8, respectively.

4.2. Feature extraction for copper strips

The method of texture spectral measure to obtain the five features is used and the plots of function $S(\theta)$ are presented in Fig. 9. It shows that the spectral measured results of seven classes of copper strips are different from each other. The texture features extracted from spectral measure are effective.

4.3. SVM classification

After obtaining the feature vectors extracted from the decomposed image, scaling them before applying SVM is very important. Sarle (1997) explains why we scale data while using Neural Networks and most of considerations also apply to SVM. Latter, the support vector machine is used to classify the 7 main defect categories in copper strip. The SVM is constructed using LIBSVM version 2.84 software (Chang & Lin, 2001). To select the kernel

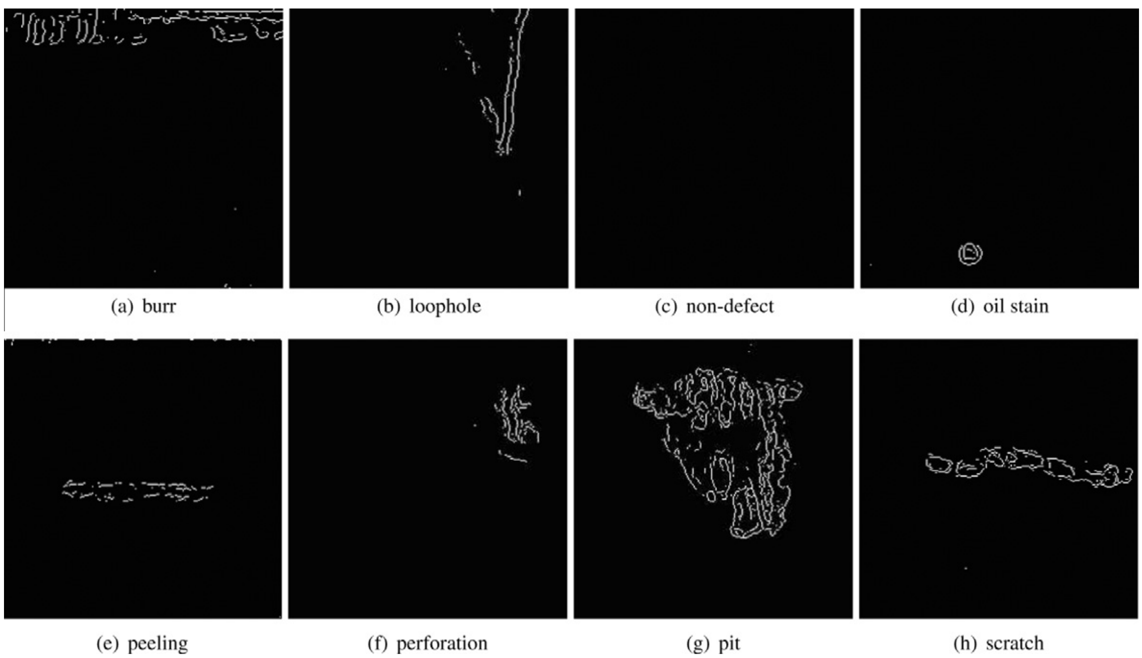


Fig. 7. Sobel filter results.

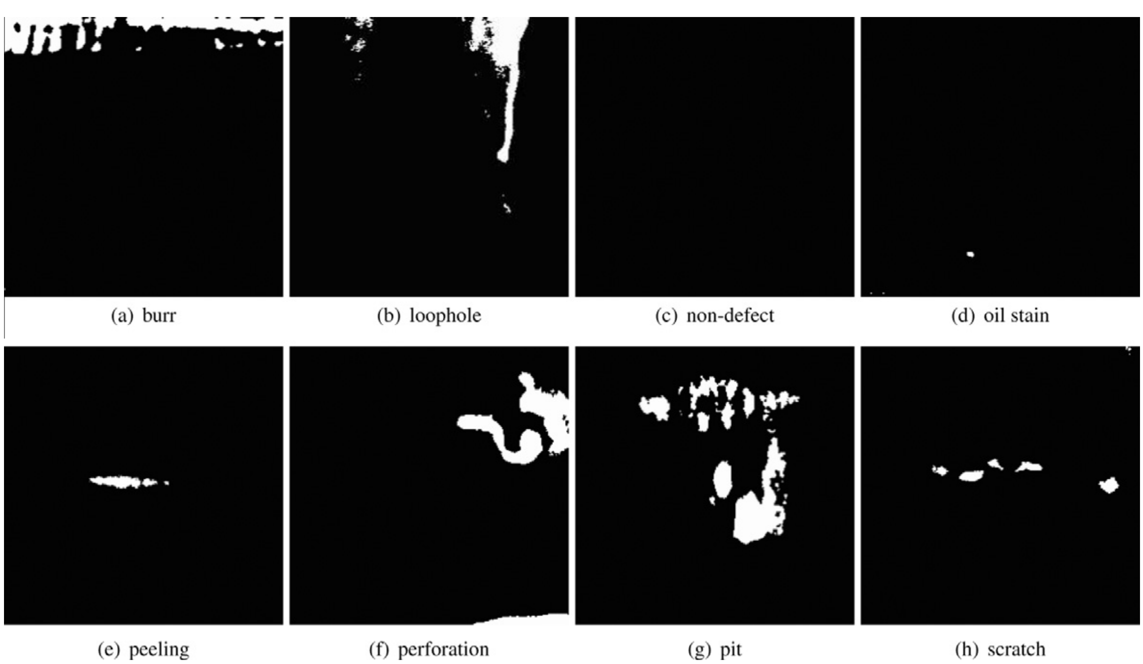


Fig. 8. Binary thresholding results.

parameter γ and penalty parameter C, we must decide which kernel to try. Because the RBF kernel nonlinearly maps samples into a higher dimensional space, so it can handle the case well when class labels and attributes are nonlinear, this will ensure a high accuracy.

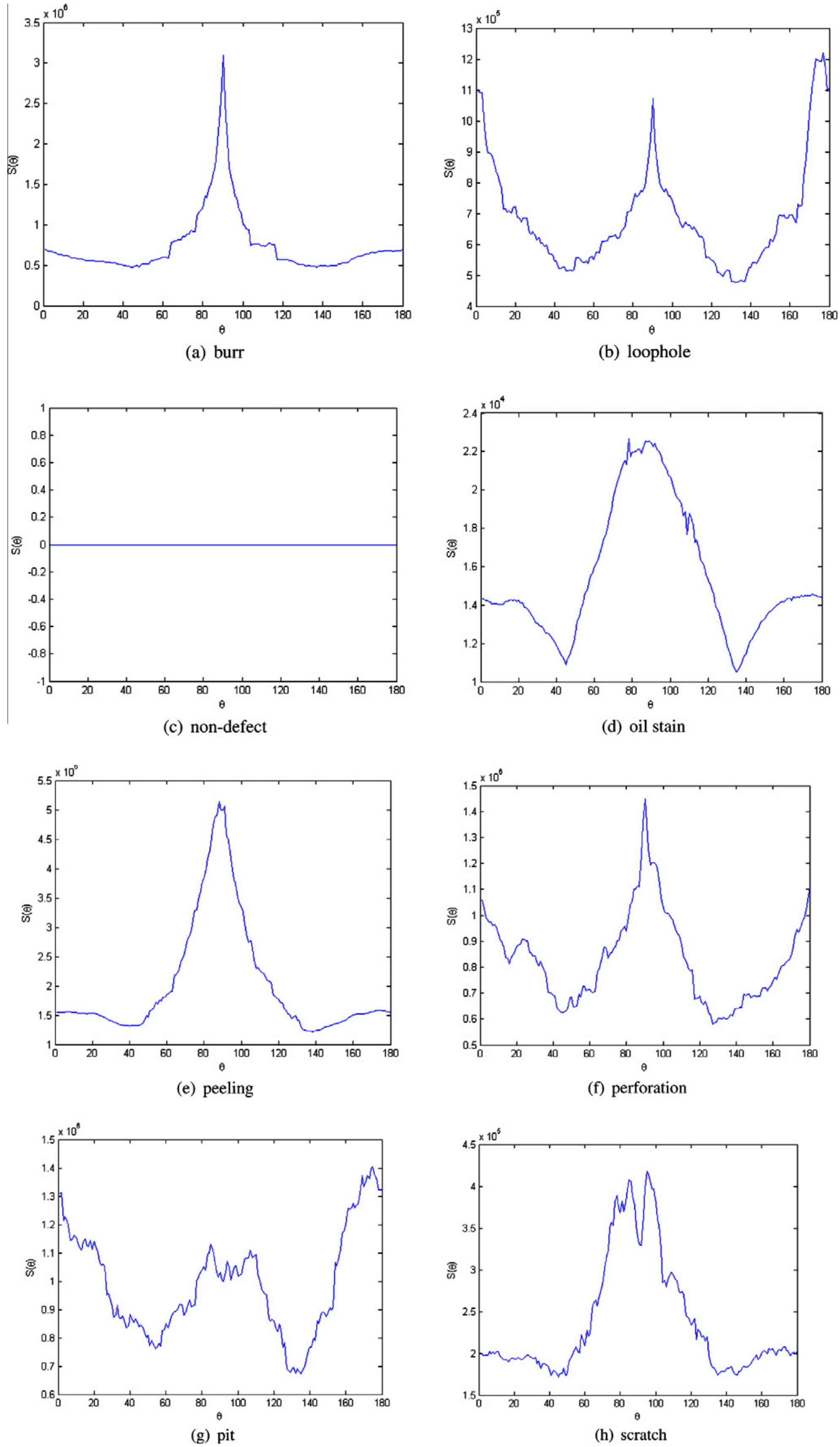


Fig. 9. Plots of function $S(\theta)$ of the eight classes.

Table 1
Cross-validation results for one-against-one.

Class	Accuracy (%)						
	$(2^6,2^{-4})$	$(2^7,2^{-3})$	$(2^8,2^{-2})$	$(2^9,2^{-1})$	$(2^{10},2^0)$	$(2^{11},2^1)$	$(2^{12},2^2)$
1 vs. 2	79.5	83.0	85.4	87.1	89.7	88.4	85.8
1 vs. 3	82.4	83.6	86.1	87.6	90.5	88.6	87.0
1 vs. 4	81.5	83.7	85.4	87.8	90.1	89.2	87.6
1 vs. 5	81.2	84.0	85.9	88.4	91.3	89.4	87.9
1 vs. 6	80.9	83.7	85.3	87.5	89.6	88.6	86.4
1 vs. 7	82.6	84.5	86.1	88.7	87.9	87.4	86.5
2 vs. 3	78.6	80.5	83.4	85.3	87.1	85.9	84.6
2 vs. 4	81.3	82.9	84.6	86.4	88.7	86.4	85.1
2 vs. 5	82.6	83.8	85.7	87.6	89.4	87.2	86.5
2 vs. 6	82.1	83.9	85.7	87.2	88.9	88.1	87.0
2 vs. 7	80.5	82.5	83.9	85.4	87.5	86.6	85.9
3 vs. 4	81.2	83.4	85.0	86.7	88.5	87.2	86.0
3 vs. 5	80.7	82.3	84.0	86.4	88.7	87.2	85.9
3 vs. 6	76.8	79.2	82.5	84.9	86.7	85.2	84.6
3 vs. 7	82.9	84.5	86.7	87.9	89.4	88.2	86.7
4 vs. 5	82.6	84.3	85.9	88.0	89.4	89.5	88.0
4 vs. 6	83.4	85.9	87.6	88.7	88.2	87.6	86.1
4 vs. 7	80.6	83.0	84.6	86.3	87.6	87.5	86.9
5 vs. 6	81.3	82.8	84.7	86.4	87.9	88.2	87.4
5 vs. 7	80.5	82.4	83.9	85.0	86.7	85.8	85.3
6 vs. 7	81.9	83.4	85.6	87.1	88.9	88.3	87.6

In LIBSVM, the authors used a "grid-search" on C and γ using cross-validation. Basically pairs of (C,γ) are tried and the one with the best cross-validation accuracy is picked. Accordingly, the parameters were set in the range of $\gamma = [2^{-4},2^{-3},\ldots,2^2]$, $C = [2^6,2^7,\ldots,2^{12}]$ to test the classification accuracy. All of the experiments were conducted using the one-against-one method (Krebel, 1999) via m-fold-cross-validation to find the best parameters, where m equal to 7. The sample set includes 420 defect images and of each class with 60 images. All of the data were divided into 2/3 training data sets (280 data) and 1/3 testing data sets (140 data).

As shown in Table 1, the cross-validation ranged from 76.8% to 91.3% by adjusting the parameter (C,γ) from $(2^6,2^{-4})$ to $(2^{12},2^2)$. Comparing with the experimental results, the best accuracy can be obtained when the parameter (C,γ) to be $(2^{10},2^0)$. So the authors used parameters $C = 1024$, $\gamma = 1$ to train the whole training set and then test it.

Table 2 shows the number of training data and test data sets for each pair using the one-against-one method. Table 3 lists the classification results using the one-against-one approach on copper strips surface defects. From Table 3, we can see that the one-against-one approach leads to high classification accuracy. Therefore, the proposed defect detection and classification method is well suited with the texture recognition of defects on strongly reflected metal surface.

In order to compare the performance of the proposed approach, we also use back-propagation neural network (BPNN) classifier to solve the same classification problem. As described in the previous section, the parameter pair of SVM are $(C,\gamma) = (2^{10},2^0)$. The network structure of BP is $5 \times 7 \times 11$. The same, the data set have been divided into 2/3 (280 images) for training, and 1/3 (140 images) for testing. The classification accuracies of SVM classifier and BPNN are shown in the Table 4, it is obvious that the SVM classifier outperforms BPNN classifier.

Table 2
Training/testing set for one-against-one method (seven classes).

Class	Training set		Testing set	
	Number of labeled +1	Number of labeled −1	Number of labeled +1	Number of labeled −1
1 vs. 2	56	24	35	5
1 vs. 3	50	30	30	10
1 vs. 4	42	38	33	7
1 vs. 5	48	32	36	4
1 vs. 6	40	40	30	10
1 vs. 7	23	57	7	33
2 vs. 3	26	54	6	34
2 vs. 4	30	50	11	29
2 vs. 5	31	49	8	32
2 vs. 6	26	54	6	34
2 vs. 7	52	28	5	35
3 vs. 4	58	22	30	10
3 vs. 5	57	23	31	9
3 vs. 6	50	30	30	10
3 vs. 7	18	62	33	7
4 vs. 5	56	24	35	5
4 vs. 6	58	22	30	10
4 vs. 7	23	57	7	33
5 vs. 6	48	32	34	6
5 vs. 7	31	49	8	32
6 vs. 7	40	40	31	9

Table 3
Classification results for one-against-one ($(C,\gamma) = (2^{10},2^0)$).

Class	Training accuracy (%)	Testing accuracy (%)	Class	Training accuracy (%)	Testing accuracy (%)
1 vs. 2	100	87.5	3 vs. 4	100	75
1 vs. 3	100	75	3 vs. 5	100	77.5
1 vs. 4	100	82.5	3 vs. 6	100	75
1 vs. 5	100	90	3 vs. 7	100	82.5
1 vs. 6	100	75	4 vs. 5	100	87.5
1 vs. 7	100	82.5	4 vs. 6	100	75
2 vs. 3	100	85	4 vs. 7	100	82.5
2 vs. 4	100	72.5	5 vs. 6	100	85
2 vs. 5	100	80	5 vs. 7	100	80
2 vs. 6	100	85	6 vs. 7	100	77.5
2 vs. 7	100	87.5	Average	100	85

Table 4
Comparison between the SVM and BP classifier.

Method	Training accuracy (%)	Testing accuracy (%)
SVM	100	85.0
BP	100	82.3

5. Conclusions

In this study, a computer vision-based system for inspection of strongly reflected metal surface defects based on wavelet transform, spectral measure, and support vector machine was developed. Multi-resolution wavelet transforms has the advantage of computational savings. During wavelet smoothing, the noise can be effectively removed from the image by setting certain detail coefficients to zero. Spectral measure method used for texture extraction characterizes seven classes of defects from each other. During SVM design, the authors used cross-validation method to get the best parameters and applied the parameters to train and test the samples. Experiments of one-against-one based defects classification have been conducted. The system is capable of identifying and inspecting the most common defects (7 defects) on the surface of strongly reflected metal. Furthermore, to evaluate the performance of the proposed method, comparison between SVM method and BPNN method has been implemented. The experimental results demonstrate that the proposed method outperforms BP neural network method. The future work should attempt to verify the effectiveness and robustness of our approach in on-line production.

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