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Automated visual inspection of surface defects based on compound moment invariants and support vector machine

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Abstract

The traditional inspection methods are mostly based on manual inspection which is very likely to make erroneous judgments due to personal subjectivity or eye fatigue, and can’t satisfy the accuracy. To overcome these difficulties, we develop a machine vision inspection system. We first compare several kinds of methods for feature extraction and classification, and then present a real-time automated visual inspection system for copper strips surface (CSS) defects based on compound moment invariants and support vector machine (SVM). The proposed method first processes images collected by hardware system, and then extracts feature characteristics based on grayscale characteristics and morphologic characteristics (Hu and Zernike compound moment invariants). Finally, we use SVM to classify the CSS defects. Furthermore, performance comparisons among SVM, back propagation (BP) and radial basis function (RBF) neural networks have been involved. Experimental results show that the proposed approach achieves an accuracy of 95.8% in detecting CSS defects.

Key words: copper strips surface (CSS) defects, compound invariant moments, support vector machine (SVM), visual inspection system, neural network

0 Introduction

Visual inspection plays an importance role in quality control in manufacturing area. Surface defects can affect not only the appearance of products but also their functionality, stability, and safety, etc. The traditional methods of defects inspection of copper strips surface (CSS) are mostly based on manual inspection, which are time-consuming and highly depend on the expertise. To deal with these difficulties, automated visual inspection system has become a hot study at home and abroad and has been widely used in surface defects inspection of fabric, steels, food, ceramic tile, etc [1-4].

Automatically visual inspection of CSS defects is extremely difficult for the following reasons: (1) CSS defects are tiny and in diverse unstructured shapes; (2) the copper strips are reflective; (3) the intensity levels of some defects change gradually. Seeing the great need and usefulness of an automatic inspection system, we design an online visual inspection system including hardware setup and software algorithms for defect detection of CSS.

Feature extraction is the key factor which directly influences defects classification in late stage of CSS defects inspection. Numerous methods have been proposed to extract features either directly from the spatial domain or from the spectral domain. Latif-Amet et al used gray-level co-occurrence matrices based on wavelet sub-image characteristics to detect defects of textile fabrics [5]. Edge, angle and area were the components of feature extraction system with parallel structure [6]. Grayscale projection was utilized for strip surface defect detection [7]. Shape characteristics, especially moments, have been widely used for pattern recognition. Hu firstly proposed the moment invariants for visual pattern recognition [8]. Then Flusser [9], Flusser and Suk [10], Khotanzad and Hong [11] did further researches on moment invariants. Difficulties exist in the feature extraction of CSS images because of the similar structure of different defects and easy misjudgment of the same defect with different scales and resolutions. Hu’s seven moment invariants retain low level characteristics of CSS images while Zernike moments can well perform high level features. Besides, both moments have good performance on invariance under translation, rotation, and scaling. In this study, we use compound moment invariants that combined Hu and Zernike moments to do feature extraction. The experiments show that the compound moments have high de-noise performance and provide general and accurate information for defects classification.

From Bayes classifier to artificial neural networks (ANN), there are many possible choices for an appropriate classifier. Ko and Kim used BP neural network and genetic algorithm to do autonomous cutting parameter regulation [12]. Several...
authors improved BP neural algorithm for classifier [13-15]. Lin and Chen used a radial basis function (RBF) neural network based classifier to recognize six universal expressions and neutral expressions [16]. De Silva et al proposed a modified RBF network architecture for holistic facial expression recognition [17].

As we know, traditional BP algorithm has some unavoidable disadvantages: (1) slow convergence; (2) the poor fault-tolerant; (3) easily getting into local minimum. The RBF network is better than BP network in terms of approaching capacity, classification, and study rate. While the SVM classifier appears to be a better choice because of its strong connection to the underlying statistical learning theory and capacity to the generalization in high-dimensional spaces. For many pattern classification applications, SVM has recently been proposed as popular tools for learning from experimental data and providing better generalization performance than other techniques [18-20].

The aim of this paper is to propose a best method to recognize the abnormal copper strips and classify the defects of CSS. After extracting features of CSS image, we apply SVM to classify the CSS defects. Furthermore, comparisons among SVM, back propagation (BP) and radial basis function (RBF) neural network have also been involved.

The remainder of the paper is organized as follows: Section 1 describes the methods of feature extraction based on morphologic characteristics, especially Hu and Zernike compound invariant moments. Section 2 compares three classification techniques based on BP neural network, RBF neural network and SVM. Section 3 demonstrates the automatic visual inspection system based on online hardware setup and proposed software algorithm. The experimental results and comparisons are also given in this section. Finally, the paper concludes with suggestions for future work.

1 Feature extraction

In this section, we first demonstrate feature extraction methods based on morphologic characteristics (Hu invariant moments and Zernike moments). Then, we compare these techniques and propose a better method for future work.

1.1 The grayscale characteristics of image

The primary methods of feature extraction based on grayscale characteristics mainly use a gray level co-occurrence matrix, which is based on the use of second-order statistics of gray level histogram. \( P(i, j) \) is the probability distribution of two pixels \((i, j)\).

In this paper, four of the most commonly used descriptors are used as features vectors.

\[
\text{Energy} = \sum_{i=1}^{n} \sum_{j=1}^{n} P(i, j)^2 \tag{1}
\]

\[
\text{Contrast} = \sum_{k=0}^{n-1} k^4 \sum_{i=1}^{n} \sum_{j=1}^{n} P(i, j) |i - j| = k \tag{2}
\]

\[
\text{Correlation} = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{ijP(i, j)}{\sigma_x \sigma_y} \tag{3}
\]

\[
\text{Entropy} = - \sum_{i=1}^{n} \sum_{j=1}^{n} P(i, j) \log[P(i, j)] \tag{4}
\]

where the means and variances in the \( x \) and \( y \) direction are given by

\[
\mu_x = \sum_{i=1}^{n} \sum_{j=1}^{n} P(i, j)
\]

\[
\mu_y = \sum_{i=1}^{n} \sum_{j=1}^{n} P(i, j)
\]

\[
\sigma_x = \sum_{i=1}^{n} (i - \mu_x)^2 \sum_{j=1}^{n} P(i, j).
\]

\[
\sigma_y = \sum_{i=1}^{n} (j - \mu_y)^2 \sum_{j=1}^{n} P(i, j)
\]

1.2 Hu moment invariants

Morphological characteristics are not only the core features of images, but also one of the important keys of human visual system to identify objects. Because shape features are stable characteristics and don’t change with the gray level of images. In image processing, the following morphological characteristics, including simple descriptors, shape descriptors, and invariant moments, are the common methods.

In 1960s, Hu introduced seven nonlinear functions defined on regular moments which are translation, scale, and rotation invariant [8]. These seven moment invariants were used in a number of pattern recognition problems.

The \((p+q)th\)-order ordinary moments and central moments of the two-dimensional density function \( f(x, y) \) are defined in terms of Riemann integral as

\[
m_{p,q} = \sum_{x} \sum_{y} x^p y^q \rho(x, y) \tag{7}
\]

\[
\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q \rho(x, y) dx dy \tag{8}
\]

where \( \bar{x} = m_{10}/m_{00} \), \( \bar{y} = m_{10}/m_{00} \), and \( f(x, y) \) is the gray value of coordinate \((x, y)\).

Then, normalization is applied to central moments, and the results are defined as \( \eta_{pq} = \frac{\mu_{pq}}{\mu_{00}} \)

where \( r = (p + q)/2 + 1, p + q = 2, 3, 4... \) These seven moment invariants can be calculated by

\[
\phi_1 = \mu_{20} + \mu_{02},
\]

\[
\phi_2 = (\mu_{20} + \mu_{02})^2 + 4 \mu_{11}^2,
\]

\[
\phi_3 = (\mu_{30} - 3 \mu_{12})^2 + (3 \mu_{21} - \mu_{03})^2,
\]

\[
\phi_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2.
\]
\[ \phi_s = (\mu_{30} - 3 \mu_{12})_2 \mu_{30} + \mu_{12}[(\mu_{30} + \mu_{12})^2 - 3(\mu_{20} + \mu_{02})^2] \\
+ (3 \mu_{21} - \mu_{03})_2 \mu_{21} + \mu_{03}[(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \\
+ 4 \mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03}) \\
\phi_0 = (\mu_{20} - \mu_{02})_2 [(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \\
+ 4 \mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03}) \\
\phi_7 = (3 \mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \\
- (\mu_{30} - 3 \mu_{12})(\mu_{21} + \mu_{03})(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \quad (9) \]

### 1.3 Zernike moments

Hu’s invariant moments present the low level information of images, while Zernike moments can describe any level of angle integers subjected to constraints: \( || \).

In 1963, Zernike proposed a set of complex orthogonal functions which can define any square integrable function in unit circle for its completeness and orthogonality. The form is presented by

\[ V_{nm}(x, y) = V_m(\rho, \theta) = R_{nm}(\rho) \exp(j m \theta) \quad (10) \]

where \( n \) is zero or positive integer, \( m \) is positive or negative integers subjected to constraints: \( n - |m| \) is even and \( m \leq n \).

\( \rho \) represents length of vector from origin to \((x, y)\) pixel. \( \theta \) represents the angle between \( x \) axis and vector \( \rho \) in counter-clockwise direction. \( R_{nm}(\rho) \) is the radial polynomial defined as

\[ R_{nm}(\rho) = \sum_{s=(|n|)}^{(|m|)} \frac{(-1)^s}{s!(n+m-s)!} \bar{R}(\rho)^{2s} \quad (11) \]

In the unit circle, any image can be uniquely defined as

\[ \rho(x, y) = \sum_{n=0}^{\infty} \sum_{m=-n}^{n} A_{nm} V_{nm}(x, y) \quad (12) \]

Complex coefficient \( A_{nm} \) is defined as the \( n \)-th Zernike moment of angle \( m \).

\[ A_{nm} = \frac{n + 1}{\pi} \int_{-1}^{1} \int_{-1}^{1} \rho(x, y) V_{nm}(x, y) \quad (13) \]

In order to gain moment invariants under translation, rotation and scaling, we must do translation and scaling normalization.

\[ g(x, y) = \left( \frac{x}{a} + x, \frac{y}{b} + y \right), a = \sqrt{s/m_{00}} \quad (14) \]

where \( m_{00}, (X, Y) \) are the area and gravity center of the image, respectively. \( s \) is an arbitrary constant.

Comparing the above methods, Hu moments and Zernike moments are invariant under translation, rotation and scaling. In this study, we propose compound moment invariants which can extract more general features for classification.

### 2 Classifier discussion

In this section, we compare three classification techniques based on BP neural network, RBF neural network and SVM.

#### 2.1 BP neural network

BP neural network is a mature and widely used network which uses the error back-propagation method to train the weights. The basic steps of the BP algorithm are as follows:

1. Initialize the weights and neural threshold of the network;
2. Disseminate forward the inputs: calculate the input and output of hidden layer and output layer

\[ \text{Input function: } I_j = \sum_i w_{ij} O_i + \theta_j \]

\[ \text{Output function: } O_j = \frac{1}{1 + e^{I_j}} \]

which maps the large value input to the range \([0, 1]\).

3. The error back-propagation: reflecting the prediction error of the network by updating the weights and biases.

The stopping criterion: (1) the values of updated weights are small enough; (2) The percent of correct classification exceeds the pre-training cycle.

#### 2.2 RBF neural network

The RBF network structure also has three layers: input layer, hidden layer, and output layer. Unsupervised learning is conducted between the input layer and the hidden layer, while supervised learning is done between the hidden layer and the output layer. The communication between hidden and output layers depends on activation levels, which is based on Euclidean distance and the equation can be written as

\[ d = R_i(\epsilon) = R_i(|\tau - \mu_i|/\sigma_i), i = 1, 2, \cdots, J \]

\( \tau \) is a multidimensional training input vector, \( J \) is the number of receptive field units, \( \mu_i \) is the objective vector for the \( i \)-th receptive field unit with the same dimension as \( \tau \), \( \sigma_i \) is a smoothing parameter greater than zero, and \( R_i(\epsilon) \) is the \( i \)-th radial basis function for the \( i \)-th receptive field unit. The most common use of \( R_i(\epsilon) \) is Gaussian function:

\[ R_i(\epsilon) = \exp \left( -\frac{|\tau - \mu_i|^2}{2\sigma_i^2} \right) \quad (15) \]

The output of the RBF network can be computed in two ways. For the first one, the output is computed by the weighted sum of the output value associated with each receptive field unit.

\[ O(\tau) = \sum_{i=1}^{J} o_i A_i = \sum_{i=1}^{J} o_i R_i(\tau) \quad (16) \]

where \( o_i \) is the connection weight between the \( i \)-th receptive field and the output unit.

The other method, the final output value is to calculate the weighted average of the output.

\[ O(\tau) = \frac{\sum_{i=1}^{J} o_i A_i}{\sum_{i=1}^{J} A_i} = \frac{\sum_{i=1}^{J} o_i R_i(\tau)}{\sum_{i=1}^{J} R_i(\tau)} \quad (17) \]

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2.3 SVM

SVM has been a popular tool for learning, because it’s more effective than other traditional nonparametric classifier, such as neural network, nearest neighbor, and K-NN classifier, in terms of classification accuracy, computational time, and stability of parameter setting. SVM obtains good generalization performance without a priori knowledge even when the dimension of input space is high.

Usually, the training example set to be classified is usually non-linear. In order to achieve the satisfied performance, the input data are mapped into a high-dimensional feature space first, and then the optimal separating hyper-plane is constructed in the feature space.

The decision function can be written as:

\[ F(x) = \text{sgn} \left( \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \right) \]  \hspace{1cm} (18)

where \( K(.) \) is Kernel function.

3 Experiments and analyses

To verify the feasibility of the proposed approach, we build up an automatic visual system and capture the CSS images using surface sensors with CCD cameras and infrared light in a laboratory environment. Six typical defects are shown in Fig.1. Fig.2 shows the hardware structure of CSS defects inspection system, which consists of surface sensor, junction box, SIS server, data server, and terminal PC. To strengthen the visibility of the images, we utilize a high resolution CCD camera (DH-HV USB 2.0 of DAHENG IMAGE Company) and an infrared lighting device (LDL-42×15 of DAHENG IMAGE Company). The CSS images are digitized into 256×256 pixels with 8-bit gray levels. The image database consists of 500 CSS images, of which 50 have no defects and 450 have various defects. The proposed approach is divided into three steps: (1) CSS images preprocessing; (2) features extraction based on compound moments; (3) SVM classification compared with two neural network classifiers.

3.1 CSS images preprocessing

CSS defects inspection is extremely difficult for dither, surface reflection, and false defects (e.g. smearing). Therefore, preprocessing is necessary. The paper uses RANSAC algorithm to stabilize the images, Curvelet transformation to remove noises from the original CSS images and a clipping method to enhance and smooth images. Take pit defect as an example, the preprocessing results are shown in Fig.3.

3.2 The proposed method for feature extraction

Compared with the multitudinous methods, this paper presents the compound moments of Hu and Zernike to extract features of CSS defects. This paper chooses pit as the sample and computes its compound moments. As shown in Table 1, these moments are invariant. Therefore, they satisfy the geometrical invariability in the range of allowable error. Table 2 shows the compound moments of six types of defects. We can see that these moments of different defects are different, which makes it easy to classify defects.
3.3 Classification results using SVM compared with BP and RBF neural network

After obtaining the features extracted from CSS defects images, SVM is used to classify six main defects of CSS compared with BP and RBF neural network classifiers. Four existing Kernel functions for SVM classifier are considered, namely, Linear, Polynomial, RBF and Sigmoid function. We evaluate the performance of the proposed method by classification accuracy. After several different experiments, we conclude that SVM with RBF Kernel function has better performance on classification.

Table 1 Compound moments of pit under different geometrical transformation

<table>
<thead>
<tr>
<th>Compound Moments</th>
<th>Moments</th>
<th>Original Image</th>
<th>Double Scale</th>
<th>Rotate 90 Degrees</th>
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Table 2 Compound moments of six types of defects

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<th>Compound moments</th>
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<th>Pits</th>
<th>Indentation</th>
<th>Holes</th>
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Table 3  Performance comparisons

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<th>Number of Incorrectly Classified</th>
<th>Percentage of Correct Classified (%)</th>
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<td>SVM BP RBF</td>
<td>SVM BP RBF</td>
<td>SVM BP RBF</td>
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<td>1 5 3</td>
<td>97.5 87.5 92.5</td>
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<td>4 7 7</td>
<td>90.0 82.5 82.5</td>
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</tr>
<tr>
<td>Indentation</td>
<td>40 39 38</td>
<td>0 1 1</td>
<td>100 97.5 97.5</td>
</tr>
<tr>
<td>Smearing</td>
<td>38 36 36</td>
<td>2 4 4</td>
<td>97.5 90.0 90.0</td>
</tr>
<tr>
<td>Total</td>
<td>230 217 220</td>
<td>10 23 20</td>
<td>95.8 90.4 91.7</td>
</tr>
</tbody>
</table>

In order to compare the performance of the proposed approach, we implement not only the BP neural network classifier with learning rate 0.01, 300 epoch and momentum 0.8, but also the RBF neural network classifier with single hidden layer (12 hidden neurons), learning rate 0.05 and spread 1.2 to classify the defects of CSS. The samples have been divided into 260 images for training and 240 images for testing. Table 3 shows the classification accuracy of three classifiers. It is obvious that SVM classifier gets the best classification accuracy of 95.8%, which is better than BP and RBF neural network classifiers with 90.4% and 91.7% accuracy in average, respectively.

4 Conclusion

Computer vision technology improves productivity and quality control in industry, and also provides a competitive advantage to industries. This paper presents an automatic visual inspection system for classification problem of detecting CSS defects using compound moments and SVM classifier. The compound moments based on Hu moment invariants and Zernike moments are invariant under translation, rotation and scaling, which can extract more general features for classification. The high generalization performance of SVM classifier without prior knowledge can map the lower feature space into higher feature space, which improves the accuracy of the classification. The experimental results show that the proposed method is capable of detecting any anticipated defects and classifying the six typical CSS defects with high accuracy according to geometrical characteristics. Comparison experiments of classification accuracy among SVM, BP and RBF neural network classifier have been conducted to demonstrate that SVM performs better than the other two methods.

Future research may improve the feature extraction and classification approach and extend the proposed method to similar defect detection problems, such as abnormal inspection of medical images.

References


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