Texture Defect Detection Using Support Vector Machines with Adaptive Gabor Wavelet Features

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Abstract

This paper aims at investigating a method for detecting defects on textured surfaces using a Support Vector Machines (SVM) classification approach with Gabor wavelet features. Instead of using all the filters in the Gabor wavelets, an adaptive filter selection scheme is applied to reduce the computational cost on feature extraction while keeping a reasonable detection rate. One-Against-All strategy is adopted to prepare the training data for a binary SVM classifier that is learnt to classify pixels as defective or non-defective. Experimental results on comparison with other multiresolution features and the Learning Vector Quantization (LVQ) classifier demonstrate the effectiveness of the proposed method on defect detection on textured surfaces.

1. Introduction

Defect detection on textured surfaces is an interesting and challenging problem. While manual inspection is still used in many industrial processes, automated visual inspection has received considerable attention by offering cost effective and high quality defect detection. Many vision-based inspection approaches have been developed to detect defects on textured materials, such as textiles [1, 2], metal surfaces [3], wood and so on [4].

Defect detection in textured materials is basically the problem of classifying pixels/blocks in the image according to the extracted features. Therefore, most of the defect detection strategies fall into a two stage scheme: 1) the extraction of features that effectively represent textures with or without defects and 2) the construction of a classifier that takes texture features as input variables to discriminate defective pixels/blocks from normal ones. Feature extraction algorithms are often categorized into model based methods, such as Markov Random Field [5, 6], statistical based methods [7], and signal processing based approaches, such as wavelet transform and Gabor filters [8, 9, 10]. There are also many choices for an appropriate classifier, such as the traditional Bayes classifiers and neural network classifiers. Among these, Support Vector Machines (SVM), pioneered by Vapnik [11], has been proved to have outstanding generalization ability in high dimensional space which is gained by its internal solution to control the learning model complexity independently of dimensionality of the feature space [12, 13].

This paper proposes a method for defect detection on textured surfaces exploring SVM with Gabor wavelet features. Gabor filters have been shown to possesses optimal localization properties in both spatial and frequency domains and have been used in various applications, such as texture segmentation [14], object detection [15], document analysis, face detection and image representation [16]. Defect detection problems are mostly texture specific problems which do not always require using a full set of Gabor wavelets. Therefore, an adaptive filter selection scheme is explored to reduce the dimension of the feature space to yield a significantly reduced image processing time.

2. Feature extraction using Gabor wavelets

A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope. The general form of a 2-D Gabor function $h(x, y)$ is defined as [17]:

$$h(x,y) = \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \cdot \exp\left[-2\pi j(u_0 x + v_0 y)\right] \quad (1)$$

where σ_x, σ_y are the standard deviations of the Gaussian function along X and Y directions which determine the filter bandwidth.

The frequency response of Gobor filter can be written as equation (2), where $\sigma_u = \frac{1}{2\pi\sigma_x}$ and $\sigma_u = \frac{1}{2\pi\sigma_x}$. (u_0, v_0) is the special central frequency of the Gabor filter.

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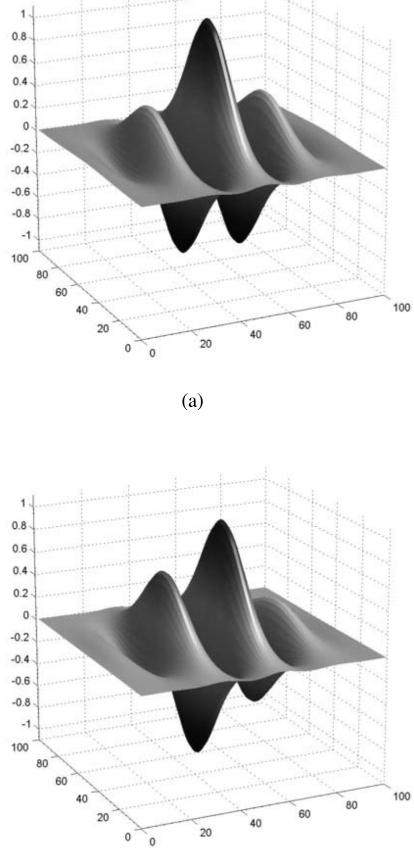


(a)

(b)

Figure 1. Gabor function in spatial domain: (a) real part (b) imaginary part

The Gabor function can be thought of as being a Gaussian function shifted in frequency to position (u_0, v_0) at a distance of $\sqrt{u_0^2 + v_0^2}$ from the origin and at an orientation of $\tan^{-1} \frac{u_0}{v_0}$.

$$H(u,v) = \frac{1}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{ -\frac{1}{2}\left[\frac{(u-u_0)^2}{\sigma_u^2} + \frac{(v-v_0)^2}{\sigma_v^2} \right] \right\} \quad (2)$$

Figure 1 shows the real and imaginary parts of the Gabor function respectively in perspective view. A class of self-similar functions, referred as Gabor wavelets, provides a multi-channel representation for image textures for forming a complete, but nonorthogonal, basis set. They can be derived from the mother Gabor wavelet $h(x, y)$ by changing the scale and orientation through the generating function [18]

$$h_{pq}(x,y) = \alpha^{-p} h(x', y'), \qquad \alpha > 1, \qquad (3)$$

where

$$x' = \alpha^{-p}\,(x \cdot \cos\theta + y \cdot \sin\theta) \quad \text{and}$$

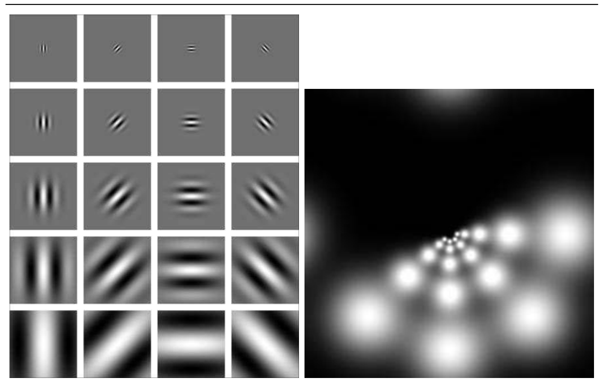
$$y' = \alpha^{-p}\,(-x \cdot \sin\theta + y \cdot \cos\theta)$$

and p and q represent p^{th} dilation and q^{th} orientation, respectively. $\theta = \frac{q\pi}{K}$ and K is the total number of orientations. The α^{-p} serves as a scale factor to ensure that every filter in the Gabor wavelets has the same energy. Figure 2 shows a set of Gabor wavelets with 5 dilations and 4 orientations in both spatial and frequency domains.

For an input image $f(x, y)$, the magnitude of filtered image $f_{pq}(x, y)$ by using $h_{pq}(x, y)$ can be calculated as follows:

$$f_{pq}(x,y) = \left\{ \left[Re\Big(h_{pq}(x,y)\Big) * f(x,y) \right]^2 + \left[Im\Big(h_{pq}(x,y)\Big) * f(x,y) \right]^2 \right\}^{0.5} \qquad (4)$$

where $Re(h_{pq}(x, y))$ and $Im(h_{pq}(x, y))$ are real and imaginary parts of $h_{pq}(x, y)$, respectively. The symbol $'*'$ denotes 2-D convolution.



(a) (b)

Figure 2. Gabor wavelets with 5 dilations and 4 orientations in (a) spatial space (real components only); (b) frequency space with each filter shown as one lobe in image

3. Support Vector Machines for classification

In this section, we review the basic concepts of SVM for two classes of classification problems. SVM is basically an approximate implementation of the *method of structural risk minimization*. The unique attribute of SVM is that it can provide an excellent generalization performance on pattern classification problems in high dimensional spaces without incorporate problem domain knowledge [12, 11, 13].

Trained by the given sample $\{(\mathbf{x}_i, d_i) \in \mathbf{R} \times \{\pm 1\}\}_{i=1}^{N}$, SVM constructs an optimal hyperplane to separate the test patterns into two classes with the margin of separation maximized. The equation of the hyperplane $g(\mathbf{x})$ is

$$g(\mathbf{x}) = \operatorname{sgn}(\mathbf{w}^T \mathbf{x} + b) \tag{5}$$

where b is the bias, and $\mathbf{w}$ is optimal weight vector which can be computed as

$$\mathbf{w} = \sum_{i=1}^{n} \alpha_i d_i \mathbf{x}_i \tag{6}$$

$\mathbf{x}_i$ are called support vectors which are a subset of the feature vectors from the training data. The coefficients α_i are *Lagrange multipliers* that maximize the following objective function

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

subject to the constraints

$$\sum_{i=1}^{n} \alpha_i d_i = 0 \quad \text{and} \quad 0 \le \alpha_i \le C \quad \text{for} \quad i = 1, 2, \cdots, N$$

where C is an user-specified positive number which controls the tradeoff between complexity of the machine and the number of non-separable points.

Considering an input space made up of nonlinearly separable patterns, the SVM is constructed by transforming the input space into a new feature space where the pattern is linearly separable in accordance with Cover's theorem on the separability of patterns. Several inner product kernels can be used to perform the transformation from the original input space to the new space. Table 1 summarizes the inner product kernels for three common types of SVMs: the polynomial learning machine, the radial-based function network, and the two-layer perceptron.

Figure 3 displays the architecture of a support vector machine. There are three layers in the architecture: the input layer, the hidden layer with inner product kernels where the input space is nonlinearly transformed into a new feature space, and the output layer which is an optimal separation hyperplane whose dimensionality is determined by the amount of support vectors.

Type of SVM	Inner product kernel
Polynomial learning machine	polynomial kernel $(\mathbf{x}^T \mathbf{x}_i + 1)^p$
Radial-basis function network	Gaussian kernel $\exp\left(-\frac{1}{2\sigma^2}\|\mathbf{x} - \mathbf{x}_i\|^2\right)$
Two-layer perceptron	hyperbolic tangent kernel $\tanh(\beta_0 \mathbf{x}^T \mathbf{x}_i + \beta_1)$

Table 1. Type of SVM and inner product kernels

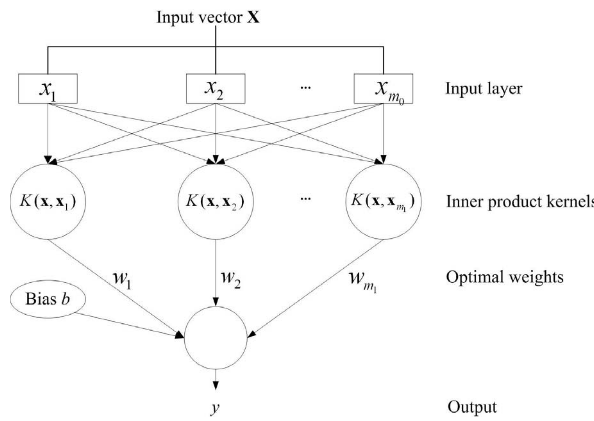


Figure 3. Architecture of Support Vector Machines

In this paper, the Gaussian kernel is used in the SVM. Preliminary results suggest the RBF network outperforms the polynomial learning machine. However, parameters such as σ and C still need to be tuned, mostly manually.

4. Adaptive filter selection

It is always desired to reduce the computational cost and image processing time without sacrificing the defect detection accuracy that is measured by classification rate. In addition, most of the defect detection problems are texture-specific. In that, each filter of the Gabor wavelets can individually provide a different response based on the subject texture. Accordingly, better discrimination quality can be achieved by selectively choosing a subset of the best fitting filters from the Gabor wavelets based on the specific texture. Manjunath and Ma introduced a feature select scheme to select a subset of Gabor filters for pattern retrieval [18]. It used the total difference energy within according spectral coverage to evaluate each filter. This selection scheme has been found suitable and used in the proposed algorithm with some modifications. For a specific texture, a Gabor filter is considered better than others if the difference of the responses on the normal area of the texture and the defective areas, ξ_{pq}, is larger.

$$\xi_{pq} = |\mu_{texture} - \mu_{defect}| \tag{8}$$

where

$$\mu_{texture} = \text{mean}\,[f_{pq}(x, y)_{texture}] \quad \text{and}$$

$$\mu_{defect} = \text{mean}\,[f_{pq}(x, y)_{defect}]$$

$f_{pq}(x, y)_{texture}$ is the filtered image of the texture under investigation by using the Gabor filter $h_{pq}(x, y)$. All other textures other than the subject texture can be reasonably viewed as various types of defects. A number of images are prepared that contain the textures other than the one under investigation to represent defects. Therefore, instead of using one image, $f_{pq}(x, y)_{defect}$ is obtained from a number of images with the same Gabor filter. Figure 4 shows the plot of the difference ξ_{pq} for a specific texture. Thus, a group of appropriate filters can be selected with larger ξ.

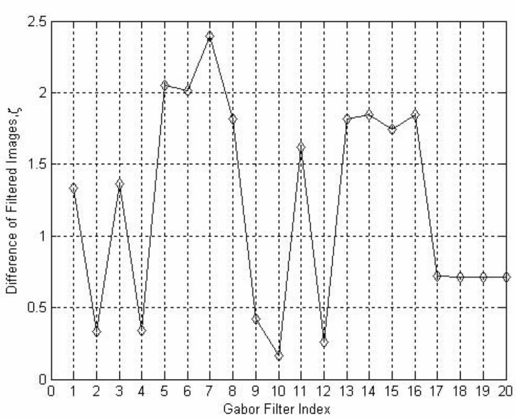


Figure 4. Gabor filter selection based on difference of filtered images, ξ_{pq}

5. Experimental results

In vision based quality assurance, defects in textured surfaces are shown as inhomogeneities of the image patterns. Any textures other than the one under investigation can be considered as defects if presented in the subject textured surface. Therefore, it is unrealistic to collect texture samples for all kinds of defects. This makes preparing training data for defects an even harder task in addition to the fact that defects are scarcely occurred in real product surfaces. To solve this problem, we use a number of textures to approximate all kinds of texture patterns of possible defects. An one-against-all strategy is applied to train the SVM which results in an optimal hyperplane to separate the feature space into two parts.

In this paper, data sets for the experiments are acquired from 50 texture samples selected from the Brodatz texture album [19]. All textures are gray scale images with 256 levels in 256×256 resolutions. Feature vectors are derived from every pixel of the images using 11×11 Gabor filter masks. Both all 20 filters in the Gabor wavelets and 8 adaptively selected optimal Gabor filters are used. A randomly selected small proportion, 2%, 4% and 6%, of the feature data are used in training the SVM classifier while the rest serve as test data. This assures no overlapping between training data and test data which would have likely resulted in an overoptimistic detection performance [20].

In this paper, the SVM classifier with Gaussian kernel is employed. The training parameters σ and C are empirically chosen at 1 and 100, respectively. The SVM is then compared with the commonly used Learning Vector Quantization (LVQ) classifier [21] in terms of classification accuracy. LVQ is an adaptive data classification method based on training data with desired class information. In the comparison, the two user-defined parameters: the number of hidden neurons and the learning rate are set as 4 and 0.1. Table 2 shows the classification results of the experiments on selected textures from the Brodatz album.

The classification rates obtained from the SVM are better than those achieved from LVQ. It is observed that the classification rates remain fairly constant when the training data proportion increases for both SVM and LVQ. With 8 optimal Gabor features, a slight decrease in the classification accuracy was shown for both classifiers. However, this is quite acceptable compared to the 60% decrease of the computational cost on the process of feature extraction.

Experimental results on defective images are shown in Figure 5. Figure 5(a,b) are images with synthesized defects. To represent any defects, the texture of the defective areas is randomly generated from the other images in the texture database. The detection results of the SVM classifier using optimal Gabor features are shown in Figure 5(c,d). The classification errors appear in form of noisy speckles which can be removed by applying a 5×5 linear filter. Figure 5(e,f) show the final detection results after filtering.

6. Conclusions

In this paper, a method for detecting defects on textured surfaces using SVM classifier is investigated. Gabor

Texture image	Training data prop. (%)	Full Gabor filters (20 features)		Optimal Gabor filters (8 features)	
		LVQ	SVM	LVQ	SVM
D77 vs. others	2	90.05	92.37	86.71	87.36
	4	89.42	92.57	85.99	87.31
	6	89.64	92.66	86.80	87.39
D4 vs. others	2	77.90	81.01	75.16	77.84
	4	76.30	81.75	75.42	77.92
	6	76.02	81.99	76.54	78.09

Table 2. Comparison of classification rate (%)

wavelet features are used as input patterns to the SVM classifier. An adaptive filter selection scheme is applied to reduce the computational cost on feature extraction while keeping a acceptable detection rate. The experimental results show the proposed method can successfully detect and segment defects in texture images. The comparison of classification rate between SVM and LVQ indicates SVM classifier has better performance. The classification results for classifiers trained with different proportions of data set show that the classification performance does not necessarily increase when the proportion of the training data increases.

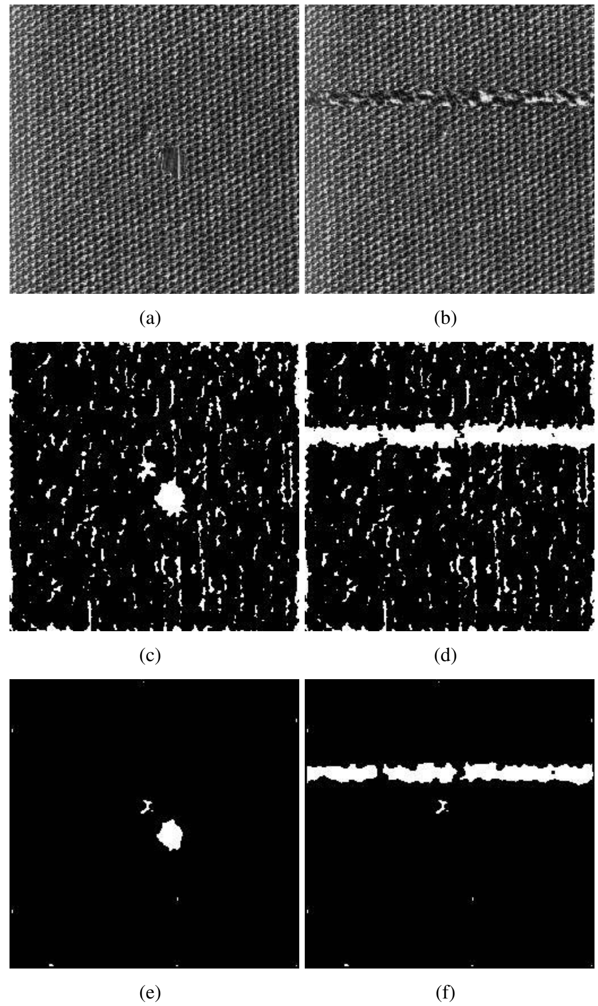


Figure 5. SVM defect detection using optimal Gabor wavelets features (a) and (b) images with defects, (c) and (d) SVM detection results, (e) and (f) SVM detection results after noise removal

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