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# An adaptive level-selecting wavelet transform for texture defect detection

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**Abstract**

We present an effective approach based on wavelet transform (WT) to detect defects on images with high frequency texture background. The original image is decomposed at various levels by WT. Then, by selecting an appropriate level at which the approximation sub-image is reconstructed, textures on the background are effectively removed. Thus, the difficult texture defect detection problem can be settled by non-texture techniques. An adaptive level-selecting scheme is presented by analyzing the co-occurrence matrices (COM) of the approximation sub-images. Experiments are done to detect the stains and broken points on texture surfaces. Comparisons with frequency domain low and high pass filters show that our method is much more effective.


*Keywords:* Wavelet transform; Co-occurrence matrix; Defect detection; Texture image processing

## 1. Introduction

More recently, visual inspection plays a vital role in assuring the quality of industrial products. Where, the objective of texture surface detection is to detect the defects such as cracks, stains, broken points, etc., on texture surfaces. Due to the repetitive changes of gray values and structures of the textures, traditional detection methods based on intensity or edge detection are invalid, which makes texture surface detection one of the most intriguing problems during the past decades and considerable attentions have been paid in this domain.

Generally, most of the previous approaches are based on clustering techniques with texture feature extraction and texture classification as two major issues. Where, the texture feature extraction techniques range from the primary statistical-based [1], model-based [2], Fourier-based [3] and Gabor filtering [4] to the latest wavelet approaches [5]. While in terms of texture classification techniques, the proximity-based classifiers [6] (such as Bayes, Euclidean distance, Mahalanobis distance, *K*-Means) and learning-based classifiers [7] (such as genetic, neural network) are successful and widely used.

However, on the one hand, among the texture feature extraction techniques, the statistical and model-based methods are, mainly, based on spatial domain processing and the features are extracted only in one single scale. Besides, the computational efficiency is a specific problem requiring extensive research. In terms of Fourier transform, which deals with the image in frequency domain, it is successful for detecting global and macro defects, however, unsatisfactory for local and micro defect detection. Then, starting from the late 1980s, due to the theoretical impact of the works of Daubechies [8], who has provided the discrete wavelet transform (DWT) and Mallat [9], who has established connection between WT and multi-resolution theory, wavelet method, which is a successful multi-resolution analysis tool in frequency domain, has received considerable attention in image processing. While on the other hand, the texture clustering techniques, proximity-based and learning-based classifiers, have unavoidable drawbacks when dealing with the vast

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image data. E.g., the proximity-based methods tend to be computationally expensive and the definition of a meaningful stopping criterion for the fusion (or division) of the data is not straightforward. Often, the learning-based classifiers need to be trained by the non-defect features, which is a troublesome procedure and usually time consuming, therefore, limits its real-time applications. In addition, it is sometimes necessary to decide the number of clusters using prior knowledge so that over-segmentation can be avoided, which often makes it neither robust nor efficient. Specially, in recent years, there are some literatures combining WT [21] with statistical approaches for feature extraction. They extract COM features from the WT sub-image for texture segmentation, which are proved to be successful [19,20,22]. However, the selection of sub-image is seldom mentioned. Besides, most of these literatures classify directly the features by classifiers such as neural networks [10], $k$-nearest neighbor classifier [11] and Mahalanobis-distance classifier [12]. Most of these classifiers need to be trained by many testing samples or defect free images, which is a troublesome procedure and usually time consuming, therefore, limits its real-time applications.

Apart from the clustering approaches, there are a few papers reporting successful applications by removing the texture patterns from original image. For example, in [13], wavelet shrinkage, which was originally proposed to remove Gaussian white noise [14], was modified to selectively remove textural information. Therefore, texture defect detection can make use of the detecting techniques developed so far for non-texture images. In [15], the eight-parameter two-dimensional adaptive lattice filter is used to perform forward prediction on the texture image, for removing the predictable part, which corresponds to the textures, in image.

These literatures, to some extent, give us some inspiration. Can we start from the viewpoint of transforming the complex texture defect detection task into a simple one? If so, how to make use of the techniques developed so far?

Fortunately, as it is known, the global textures are repetitive patterns with high frequency, so, if we can remove the textures from the original image, the texture background can be transformed into a smooth one. Starting from this viewpoint, in this paper, WT, which is a successful multiscale tool in frequency domain but the selection of decomposition levels has never been mentioned in prior studies, is employed to decompose the original image at various levels. By analyzing one COM feature of the approximation sub-images, the appropriate level, at which the approximation sub-image can be reconstructed into a non-texture image, is determined. Then the detection task can be accomplished by non-texture techniques. Several wavelet bases are tested for this task and experiments are done on defective texture surfaces. Comparisons with traditional approaches show the good performance of the adaptive WT scheme.

The rest of this paper is organized as follows: in Section 2, the mathematical basis of multi-scale WT and COM is briefly reviewed. Then, the adaptive level-selecting scheme based on WT and COM is elaborated in Section 3. After that, in Section 4, experiments are done to detect the stains and broken points on texture surfaces. Finally, concluding remarks are given in Section 5.

## 2. Mathematical basis

### 2.1. WT

WT is defined as the inner product of a signal (image) with a family of real orthogonal basis functions, $\psi_{a,b}(x)$, obtained by translation and dilation of a kernel function, $\psi(x)$, known as mother wavelet

$$\psi_{a,b}(x) = \frac{1}{a}\psi\left(\frac{x-b}{a}\right) \tag{1}$$

where $a$ is the dilating factor and $b$ is the shifting factor.

Generally, WT of function $f(t)$ is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function $\psi$

$$W_{a,b} = < f, \qquad \psi_{a,b} >= \sum_t f(t)\psi_{a,b}(x) \tag{2}$$

The results of the WT are many wavelet coefficients $W$, which are functions of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal

$$f(t) = \sum_{a,b} W_{a,b}\psi_{a,b}(x) \tag{3}$$

With WT, a signal can be decomposed into approximations, which represent the low frequency parts of the signal, and details, which account for the high frequency parts. While multi-scale wavelet transform can be implemented as a pyramid or tree structure. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. Let $cA_n$ be the approximation, $cH_n$ the horizontal, $cV_n$ the vertical and $cD_n$ the diagonal coefficients of $n$-level wavelet decomposition. Then, the reconstructed approximation and detail sub-images can be represented by the following formula:

$$A_n = \sum_{n,b} cA_n\psi_{n,b}(x) \tag{4}$$

$$H_n = \sum_{n,b} cH_n\psi_{n,b}(x) \tag{5}$$

$$V_n = \sum_{n,b} cV_n\psi_{n,b}(x) \tag{6}$$

$$D_n = \sum_{n,b} cD_n\psi_{n,b}(x) \tag{7}$$

Fig. 1 illustrates the four level decomposition of an image, where $A$ is the approximation of (a), $H$ represents the horizontal sub-image, $V$ corresponds to the vertical sub-image and $D$ accounts for the diagonal sub-image.