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ScienceDirect
Image and Vision Computing 25 (2007) 1785–1801
www.elsevier.com/locate/imavis

Automated visual inspection of ripple defects using wavelet characteristic based multivariate statistical approach

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Received 13 June 2005; received in revised form 1 January 2007; accepted 2 February 2007

Abstract

This paper presents a wavelet characteristic based approach for the automated visual inspection of ripple defects in the surface barrier layer (SBL) chips of ceramic capacitors. Difficulties exist in automatically inspecting ripple defects because of their semi-opaque and unstructured appearances, the gradual changes of their intensity levels, and the low intensity contrast between their surfaces and the rough exterior of a SBL chip. To overcome these difficulties, we first utilize wavelet transform to decompose an image and use wavelet characteristics as texture features to describe surface texture properties. Then, we apply multivariate statistics of Hotelling T^2, Mahalanobis distance D^2, and Chi-square X^2, respectively, to integrate the multiple texture features and judge the existence of defects. Finally, we compare the defect detection performance of the three wavelet-based multivariate statistical models. Experimental results show that the proposed approach (Hotelling T^2) achieves a 93.75% probability of accurately detecting the existence of ripple defects and an approximate 90% probability of correctly segmenting their regions.

Keywords: Detection of ripple defects; Machine vision; Hotelling T^2 multivariate statistics; Wavelet characteristics

1. Introduction

This research aims to construct a machine vision system for inspecting ripple defects in surface barrier layer (SBL) chips, one kind of work in process of ceramics capacitors. Ripple defects, commonly found in the randomly textured surfaces of SBL chips, are formed by the steam generated during the production process. The defects affect the appearances of SBL chips as well as the electronic properties of the products. Difficulties exist in automatically inspecting ripple defects because: (1) ripple defects are semi-opaque; (2) ripple defects have unstructured shapes; (3) the intensity levels of a ripple defect change gradually; (4) the surface of a SBL chip is rough and its intensity levels are close to those of its ripple defects (low contrast). As seen in Fig. 1, the three images contain ripple defects of different shapes and the intensity levels of the defects change gradually. Nevertheless, difficulties also exist in detecting ripple defects by human eyes because inspectors are very likely to make erroneous judgments due to personal subjectivity or eye fatigues. Seeing the great need and usefulness of an automatic inspection system, we apply wavelet transform and multivariate statistical models to construct a machine vision system for detection of ripple defects.

Texture analysis, an important step in the image processing procedure, can be applied in various areas, such as diagnosing pathological changes of tumor cells in medical images, detecting surface defects of industrial parts, and remote sensing. The main tasks of texture analysis involve classification, segmentation, and synthesis [1]. Textures are generally classified into two categories: structural and statistical [2]. Structural textures consist of repetitions of some basic texture primitives, such as lines, arcs or circles, with a definite displacement rule. They have regular and homogeneous properties and arise commonly in textile

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doi:10.1016/j.imavis.2007.02.002

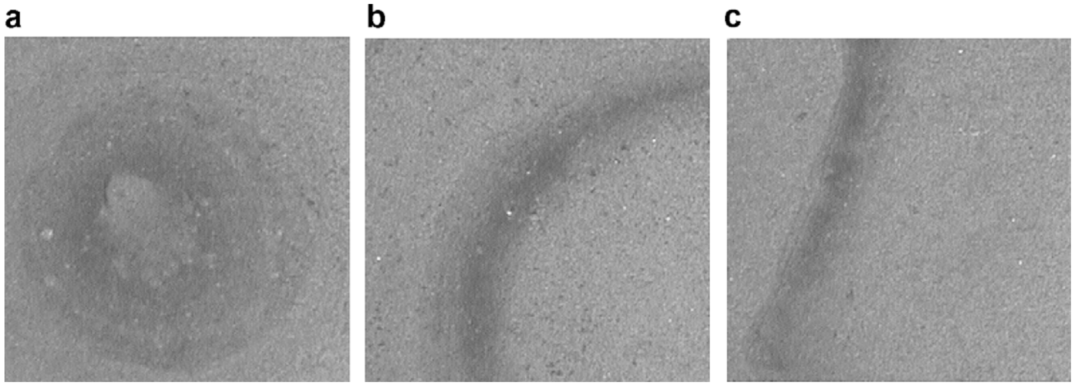

Fig. 1. Ripple defects of different shapes.

fabrics and machined surfaces. Numerous methods have been designed to solve the structural defect inspection tasks in textile fabrics [3–5]. On the other hand, statistical textures, also called random textures, cannot be described by primitives and displacement rules. They arise randomly in object surfaces, such as sandpapers, leathers, and cast surfaces. Surface defects locally break the homogeneity of a texture pattern. In general inspection of random textures [6–10], most researchers do not consider how the gradual changes of image properties impact the defect inspection results, even if some defects do have gradual changes of image properties. In this research, we present a wavelet-based multivariate statistical approach for inspecting semi-opaque, unstructured and low contrast ripple defects that have gradually changing intensity levels at their edges.

Automatic techniques for the visual inspection of textured surfaces usually compute a set of textural features in a sliding window and search for significant local deviations in the feature values. Generally, there are two types of texture analysis techniques: spatial domain and frequency domain. The traditional method for texture analysis in the spatial domain is to extract various features from a gray level co-occurrence matrix. This approach is based on the use of second-order statistics of the grayscale image histogram. Siew et al. [11] use two-order gray level statistics to build up probability density functions of intensity changes, and develop co-occurrence matrices for carpet wear assessment. Also, Venkat Ramana and Ramamoorthy [12] present the co-occurrence matrix based statistical methods to compare the texture features of machined surfaces.

Fourier transform, Gabor transform and wavelet transform are common texture analysis techniques used in the frequency domain [1]. Fourier-based methods characterize the spatial frequency distribution of textured images, but they do not consider the information in the spatial domain and may ignore local deviations [10]. Chan and Pang [13] introduce the central spatial frequency spectrum approach to classify four defects of textile fabrics based on seven characteristic parameters of the Fourier spectrum. Gabor-filter-based approaches have been successfully applied for texture analysis [9,10], but the design of optimal Gabor filters is a complicated task and these methods are computationally expensive since the 2-D convolution must be conducted in a sliding window throughout the entire image. In addition, Gabor filters require proper tuning of filter parameters at different scales [14]. Kumar and Pang [15] propose supervised and unsupervised defect detection approaches for automated inspection of textile fabrics using Gabor wavelet features.

Wavelet transform provides a convenient way to obtain a multiresolution representation, from which texture features are easily extracted. It has been a popular alternative for the extraction of textural features. Since images in different scales and frequencies have inherent characteristics for the appearance of a texture, the multi-resolution, multi-channel modeling capability of wavelets is well suited for texture analysis [16]. The use of the wavelet transform for texture analysis was pioneered by Mallat [17]. Textureal features extracted from wavelet-decomposed images are widely used for texture classification, segmentation, object recognition, and defect detection [18–21]. Latif-Amet et al. [22] propose a sub-band domain co-occurrence matrix method for texture defect detection. Their approach is performed first by decomposing the gray level images into sub-bands, then by partitioning the textured image into non-overlapping sub-windows and extracting the co-occurrence features and finally by classifying the defective sub-windows with statistical classifier. Huang and Aviyente [23] develop an algorithm to choose independent subbands to form a sparse representation of texture images for classification. Cui et al. [24] propose an effective method for rotation and scaling invariant texture classification based on wavelet analysis in the Radon domain.

Color and texture are two of the most important properties in analyzing complicated material surfaces. Color can provide powerful information for texture analysis, but traditional texture analysis techniques are inappropriate for colored texture images because they ignore chromatic information. More sophisticated color imaging methods have been developed for color texture classification and defect detection [25,26]. Wouwer et al. [27] introduce wavelet energy-correlation signatures extracted from features of wavelet-decomposed images for color texture characteriza-