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Fast defect detection in homogeneous flat surface products

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ABSTRACT

This paper introduces a novel hybrid approach for both defect detection and localization in homogeneous flat surface products. Real time defect detection in industrial products is a challenging problem. Fast production speeds and the variable nature of production defects complicate the process of automating the defect detection task. Speeding up the detection process is achieved in this paper by implementing a hybrid approach that is based on the statistical decision theory, multi-scale and multi-directional analysis and a neural network implementation of the optimal Bayesian classifier. The coefficient of variation is first used as a homogeneity measure for approximate defect localization. Second, features are extracted from the log Gabor filter bank response to accurately localize and detect the defect while reducing the complexity of Gabor based inspection approaches. A probabilistic neural network (PNN) is used for fast defect classification based on the maximum posterior probability of the Log-Gabor based statistical features. Experimental results show a major performance enhancement over existing defect detection approaches.

1. Introduction

Machine vision introduces powerful techniques for automated visual inspection (AVI) of flat surface products such as textiles, wall paper, foils, ceramic tiles, lumber, leather and other products. The major challenges in designing an automated inspection system are the fast speed required to cope with the production line speeds and the variable nature of defects encountered during the production process. For defect detection of flat surface products, the texture of product surface has to be accurately analyzed using the texture characterization techniques. Table 1 summarizes the most recent approaches reported in the literature for texture characterization and defect detection. Excellent overviews of the previous work on defect detection could be found in Alameldin (1988), Schicktanz (1993), Xie (2008), Kumar (2008).

This paper presents a hybrid approach that is based on the statistical decision theory, descriptive statistics, Log-Gabor filter-banks and the probabilistic neural network (PNN).

This paper is organized as follows: Section 1 gives an introduction to AVI and an overview of the most recent AVI approaches. Section 2 describes the role of the coefficient of variation as a homogeneity measure for approximate and faster defect detection. Section 3 presents the architecture of the proposed defect detection system. Section 4 describes the Log-Gabor based feature sets used for accurate defect detection and localization. Section 5 describes the design and architecture of the probabilistic neural network classifier. Section 6, presents the experimental results and their discussion. In Section 7, the system performance is evaluated. Finally, concluding remarks are given in Section 8.

2. Approximate defect localization using the coefficient of variation

Homogeneity reflects the uniformity of gray level distribution within a region of an image. It can be used both for selecting the training set in defect detection applications and guiding the defect detection process in the regions of interest (ROIs). In Cheng and Sun (2000), homogeneity is defined as a composition of both the standard deviation and discontinuity of gray level intensities. Standard deviation σ_{l_i} describes the contrast within a local region i at level l. Discontinuity is a measure of abrupt changes in gray levels and can be obtained by applying edge detectors to the corresponding region. Performing analysis of the homogeneity measure according to Fig. 1 and Table 2, the computational complexity of the processing could be drastically reduced, especially in the case of defect detection in homogeneous product surfaces like raw textiles.

Fig. 1 shows the image pyramid for a texture extracted from the TILDA database (TILDA, 1996). Table 2 gives the standard deviation σ_{l_i} of the image blocks at three successive levels L0, L1, and L2. At level L1 it is observed that the largest gray level variation occurs in the fourth quarter of the original image l_4 at level L1. Further division at level 2 shows that the least homogeneous image section exists in the second quarter l_2 at level L2. The coefficient of variation is given by

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Table 1
Ranking the performance of different feature extraction approaches.

Feature extraction approach	PCC (%)	Rank	Reference	Feature extraction approach	PCC (%)	Rank	Reference
Gabor	87.89	3	Chen, Chen, and Chen (2006)	Multiresolution histograms	N/A	1	Cheng and Sun (2000)
Wavelet97	88.15	1		Fourier power spectrum annuli	N/A	2	
Wavelet54	88.02	2		Gabor wavelet features	N/A	3	
Daub4	75.65	4		Daubechies wavelet packets features	N/A	4	
Haar	73.57	5		Auto-co-occurrence matrices 11×11 pixels	N/A	5	
Ordinary histogram	77.54	8	Monadjemi (2004)	Markov random field parameters 3x3 window	N/A	6	
LBP	84.18	7		GLCM	33.3	5	Haralick, Shanmugam, and Dinstein (1973)
GLCM	97.09	1		FFT	48.3	4	
Gabor filter	91.22	6		Wavelet transform	80	3	
DWHT	95.58	4		Gabor transform	85	2	
DDCT	95.14	5		Clustering	91.6	1	
Eigenfilter $N = 7 \times 7$	95.70	3		Gabor	72.30	2	Jenicka and Suruliandi (2008)
GC	97.02	2		Complex directional filter bank	72.69	1	
GLCM	72.5	3	Pieczynski, Augustin, Karoui, Fablet, and Boucher (2008)	Steerable pyramids	69.06	4	
LBP	85.83	1		Contour	71.53	3	
Texture spectrum	82.17	2		Gabor	77.2	3	Basıbüyük1, Çoban, and Ertüzün (2007)
				GLCM	95.05	2	
				Selected from gabor and GLCM	96.9	1	

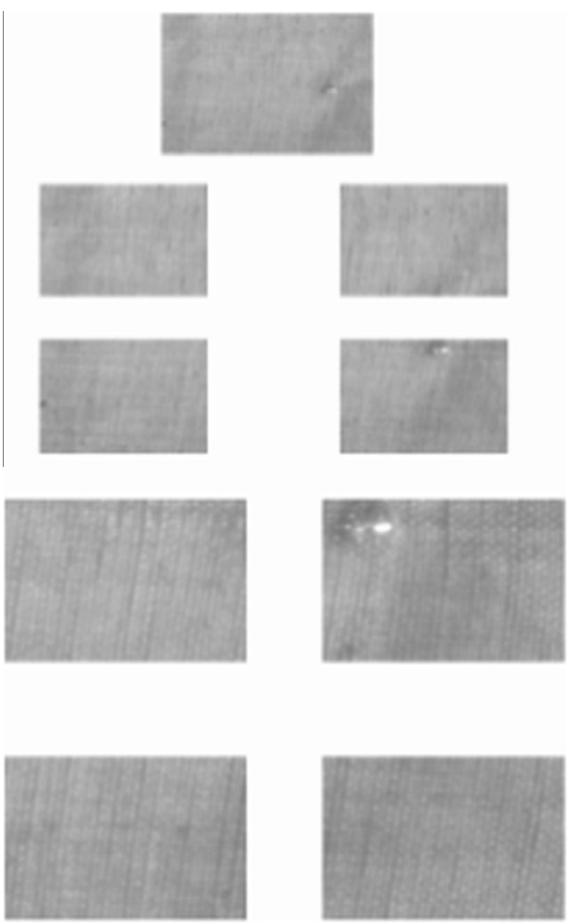

Fig. 1. Multi-resolution homogeneity based localization of defects.

$$c_v = \frac{\sigma}{\mu} \times 100, \qquad (1)$$

where σ is the standard deviation of gray levels within an image block and μ is the mean gray level of that block. Bold values represent large standard deviations of defective blocks compared to their neighboring blocks.

Table 2
Standard deviation σ_{l_i} of ROI at different pyramid levels.

Level	σ_{l_i}			
L0	10.9253			
L1	l_1 7.5989	l_2 9.8759	l_3 8.9331	l_4 ***11.7519***
L2	l_1 8.3183	l_2 ***12.3536***	l_3 9.3111	l_4 8.0230

Bold numbers indicate the standard deviation at defective blocks.

3. Defect detection system architecture

Fig. 2 shows the main components of the proposed defect detection system in flat surface products. First, a high resolution gray level image of the flat surface is acquired. Approximate detection and localization of the defect is performed using the coefficient of variation c_v of image blocks of suitable size. The coefficient of variation is used as a homogeneity measure. Normal surface blocks result in small values of c_v. Abnormal blocks show increased c_v values. A second stage that is based on features extracted from the Log-Gabor filtered image blocks is used for more accurate defect detection and localization. For each inspected image block, 18 features are extracted and fed into a PNN classifier for fast and noise immune defect detection.

4. Log-Gabor filter based feature extraction

Field (1987) presented the Log-Gabor function as an alternative to the Gabor function because log Gabor functions have extended tails that renders them more efficient in encoding natural images than the ordinary Gabor functions (Field, 1987; Kovesi, 1996). Features extracted from blocks convolved with Gabor filters have been used to detect responses to global textural variation. Both the ability of Gabor filters to approximate certain characteristics of how information is processed in the primary visual cortex (Turner, 1986) in addition to their optimal localization properties in both