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Automated defect detection in uniform and structured fabrics using Gabor filters and PCA

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ABSTRACT

This paper describes an algorithm for texture defect detection in uniform and structured fabrics, which has been tested on the TILDA image database. The proposed approach is structured in a feature extraction phase, which relies on a complex symmetric Gabor filter bank and Principal Component Analysis (PCA), and on a defect identification phase, which is based on the Euclidean norm of features and on the comparison with fabric type specific parameters. Our analysis is performed on a patch basis, instead of considering single pixels. The performance has been evaluated with uniformly textured fabrics and fabrics with visible texture and grid-like structures, using as reference defect locations identified by human observers. The results show that our algorithm outperforms previous approaches in most cases, achieving a detection rate of 98.8% and a false alarm rate as low as 0.20–0.37%, whereas for heavily structured yarns misdetection rate can be as low as 5%.

1. Introduction

In the textile industry, defect detection is of crucial importance in the quality control of manufacturing [1]. The traditional inspection process still depends mainly on human intervention. This nature of work is dull and repetitive, and the relatively hostile working environment near the weaving machines is not suitable for human inspection [2]. The accuracy of human visual inspection declines with monotonous jobs and endless routines. In order to lower the costs of this process and to increase the competitive advantage of the products, it is necessary to automate the inspection step. Automated fabric inspection systems, albeit very expensive, are currently available. State-of-the-art systems are BarcoVision's Cyclops, Shelton webSPECTOR, Elbit Vision System's I-Tex, Zellweger, Uster's Fabriscan, and MQT. These systems have been described in [3] but details about the used algorithms have not been disclosed due to the intellectual property constraints.

Automated fabric defect detection methods and the used approaches can be classified in seven categories: statistical, spectral, model-based [1,4], learning, structural, hybrid, and motif-based [5]. Spectral approaches are particularly suitable due to the high degree of periodicity of yarns in textile fabric, which permits the use of spectral features for the detection of defects. In spectral-domain approaches, texture features are generally derived from Fourier transform, wavelet transform, and Gabor filters.

Due to the noise immunity and enhancement of periodic features, Fourier analysis based approaches have been developed [6]. However, since the kernel function of Fourier transform is of infinite length, the contribution from each of the spectral components is difficult to quantify; therefore, spectral techniques other than Fourier analysis appear to be more suitable for detecting local fabric defects.

The wavelet transform has been used [7,8] to decompose images in the spatial domain into a hierarchy of localized sub images at different spatial frequencies. Compared with the traditional Fourier analysis, the wavelet transform provides both frequency and spatial local information about an image. In [9] a fabric defect detection scheme has been described, using wavelet analysis on two 1-D projection signals to reduce the amount of data processing.

Gabor analysis has been widely used to extract local frequency information from an image. Unlike Fourier analysis, which determines a global frequency domain representation of the entire image, Gabor filters estimate the strength of certain frequency bands and orientations at each location in the image, giving a result in the spatial domain [10]. Gabor filters are a popular tool for image analysis, and have found widespread use in computer vision. Applications have included face tracking [11], face and object recognition [12,13], texture analysis [14,15], and image denoising [16]. Their use is supported by neurophysical studies that have suggested that behavioral receptive fields of the simple cells in the primary visual cortex can be well approximated by Gabor filters.

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The drawback of Gabor filtering in computer vision is the required computational load. Applying a Gabor filter to an image involves convolution with a set of Gabor wavelets, consisting of numerous kernels at different wavelengths and orientations. While the cost of performing these convolutions can be significantly reduced by separability, the total computation time is often still high.

The literature reports several Gabor filter-based detection approaches. In [17–20] a multichannel filtering scheme based on Gabor filter bank has been proposed. Kumar and Pang [17] used a set of filters, which were derived from the real parts of Gabor wavelets from 16 different channels in four orientations, to detect fabric defects. In [18,19], complex Gabor filters have been applied to textile web inspection. In [20] a multichannel Gabor filter approach, with modified Principal Component Analysis (PCA) to select the relevant features and one-class classification techniques, has been described, but performance has been reported only in terms of visual assessment. Basturk et al. [21] applied Gabor wavelets on images divided in windows, in order to extract texture features, and PCA was used to reduce the dimension of feature vectors.

Recently, Zhang et al. [22] proposed Gabor filters in order to extract the foreground mask and texture features, integrated with a Gaussian mixture model for fabric defect detection and classification. Gabor filter parameters can also be selectively optimized to discriminate different defects, and optimal filters can be used [23–25]. In [9] an adaptive threshold technique based on optimal Gabor filter for online defect detection in various textiles is presented. In an optimal filter, its parameters are tuned to match a particular texture background; therefore, fewer filters are needed and less time is required for filtering. The authors in [23,24] use the response to a single input image in order to select the optimal filter from a set of filters. In [26] a Gabor wavelet network is used to extract optimal texture features from a nondefective fabric image. The detection scheme consists of three real-valued filters and one smoothing filter. Although optimal filters have some obvious advantages over other methods, the selection of their parameters is crucial and difficult. Another approach for selecting Gabor filter parameters is reported in [27], where an odd-symmetric filter is designed to match with the texture features of defect-free fabric image; single-scale odd Gabor filters are also used in [28] for purposes of edge detection, but the feature identification and dimension reduction strategies are based on mean and variance threshold comparison of the edge pixels statistical distribution.

In this paper, we extend the work presented in [29] by exploiting the performance of Gabor filters considering an algorithm devoted to detect texture defects, the dimension and orientation of which vary randomly in uniform and structured fabrics.

The main features of our approach are that the analysis is performed on a patch basis, and that the defect identification phase is based on the Euclidean norm of feature vectors and on the comparison with fabric type specific parameters. The algorithm has been evaluated with uniformly textured fabrics and fabrics with visible texture and grid-like structures.

The paper is organized as follows. Section II describes the algorithm, based on a complex symmetric Gabor filter bank, where the filtered images have been divided into nonoverlapping patches, instead of operating on single pixels as in previous works [17,18]. This is beneficial to reduce noise influence on defect detection. The nonlinear function used to rectify filter responses is the magnitude function, which has a relatively low computational complexity. A discussion on the selection of the parameters used in the algorithm has been reported in Section III. In Section IV the performance obtained using images of the TILDA Textile Texture Database [30] has been evaluated, in order to compare the results obtained considering different parameters for the Gabor filters. A set of images has been also visually inspected and manually annotated by human observers, in order to provide a ground-truth reference for the algorithmic performance. Eventually, the results have been compared with those of other algorithms reported in the literature, showing an improvement. Previous works have rarely been based upon an extensive comparative evaluation of publicly available datasets. Therefore, we believe that the results of these experiments will be a valuable resource for future works in this area.

2. Algorithm description

The algorithm consists of two main steps: (i) calibration and (ii) image inspection. The calibration procedure, which uses parts of the inspection procedure, must be executed using defect-free images, in order to obtain the parameters adopted in the algorithm, which are characteristic of fabric types. The proper evaluation of these parameters maximizes system performance and reduces the probability of false alarms. In the inspection procedure, image features are extracted using a complex symmetric Gabor filter bank, the filtered images are divided into nonoverlapping patches, and defect segmentation is performed on blocks of pixels. The dimension of patch feature vectors, obtained by fusing multiple images, has been reduced applying PCA. In the following, most of the used parameters result from empirical tests: for instance, block size, orientations and dyadic bands, Gabor kernel size, reduced feature vector size have been selected after an extensive simulation tuning. For the sake of clarity, we will describe the inspection phase first, and the calibration phase afterwards.

2.1. Image inspection

The block diagram of the image inspection algorithm is shown in Fig. 1. The image $I(x, y)$, of size $N_1 \times N_2$ pixels, is first gain-corrected, to remove artifacts due to nonhomogeneous lighting and camera lens dirt. A number of M defect-free images $F_m(x, y)$, $m = 0, \ldots, M-1$, have been averaged and smoothed with a 5×5 Gaussian filter $h(x,y)$. The correction gain (Fig. 2b), $G(x, y)$, has been computed by inverting the smoothed average (the smoothing kernel is used to remove the effect of any remaining fabrics texture and to avoid mathematical precision problems when inverting) and normalizing it, in order to maintain the same luminance level, as

$$G(x,y) = \frac{A_{avg}}{A(x,y)} \tag{1}$$

$$A(x,y) = \left(\frac{1}{M} \sum_{m=0}^{M-1} F_m(x,y) \right) * h(x,y) \tag{2}$$

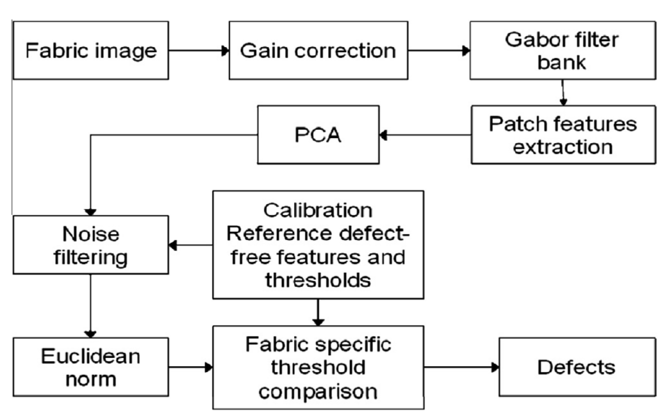

Fig. 1. Block diagram of the proposed approach.