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Differential evolution-based optimal Gabor filter model for fabric inspection

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ABSTRACT

In this paper, a defect detection model using optimized Gabor filters, which is suitable for real-time operation, is proposed to tackle the woven fabric inspection problem in fashion industry. Based on the analysis of the particular characteristics of fabric defects, the proposed model utilizes composite differential evolution (CoDE) to optimize the parameters of Gabor filters, which can achieve the optimal feature extraction of fabric defects. Together with thresholding and fusion operations, the optimal Gabor filters can successfully segment the defects from the original image background. By using optimal Gabor filters instead of a Gabor filter bank, the computational cost of the detection model can be significantly reduced. The performance of the proposed defect detection model is evaluated off-line through extensive experiments based on various types of fabric. Experimental results reveal that the proposed detection model is effective and robust, and is superior than four existing models in terms of the high detection rate and low false alarm rate.

1. Introduction

In the textile and clothing industry, woven fabric defects refer to the inhomogeneous areas that appear on the woven fabric surface texture. Fabric defects can be categorized into more than 70 types [28]. Normally, the income loss caused by fabric defects can be up to 45–65% [33]. Therefore, in both fabric mills and apparel companies, fabric quality control plays a significant role in the manufacturing process. Traditionally, the fabric inspection is carried out by visual checking of human operators with high labor cost. In addition, the inspection performance is unreliable due to the fact that very small defects cannot be identified and human error caused by fatigue happens. According to the previous research, the accuracy of human inspection in textile industry is merely 60–75% [33]. As a result, it is necessary to develop vision-based automated inspection systems for fabric defect detection.

Fabric defect detection is usually considered as a texture analysis problem since fabric surface can be recognized as two-dimensional (2-D) patterned texture. Over the past three decades, with the utilization of digital images of woven fabrics, various vision-based approaches have been proposed to address this problem. Basically, these approaches can be classified into four groups: statistical, structural, model-based and spectral approaches [28]. Firstly, statistical methods usually use first-order statistics (i.e., mean and variance), and second-order statistics (i.e., auto-correlation function and co-occurrence matrices) to represent textural features in texture discrimination [9,32,7,21]. However, it is very challenging to discriminate subtle defects from the standard textile texture by barely utilizing features of gray levels. Secondly, structural methods consider texture as a composition of textural primitives. Texture analysis is implemented by extracting the texture elements and inferring their replacement rules [6]. Unfortunately, these approaches are only effective in segmenting defects from texture whose pattern is very regular. Thirdly, in model-based approaches, autoregressive model and Markov random field are two common techniques applied in exploiting the relationship between pixels in a textural image [1,29]. Similar to statistical approaches, model-based methods also do not perform effectively in detecting small defects (local defects). Finally, regarding yarns as basic texture primitives, spectral methods address fabric defect detection in the frequency domain by utilizing spectral features of images. Among the four classes of methods, spectral methods are the most widely utilized ones in fabric defect detection [5,18,20], since textural features extracted in the frequency domain are less sensitive to both noise and intensity variation than that in the spatial domain.

In general, the techniques involved in spectral methods are Fourier transform, wavelet transform and Gabor transform, which are described in detail as follows. (1) Texture pattern can be extracted by analyzing the frequency spectrum of fabric sample

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images. In Tsai and Hsieh [40], normal fabric pattern texture could be eliminated by detecting high-energy frequency components in the Fourier domain image. As a result, fabric defects were featured in the residual image. In Chan and Pang [5], based on the three dimensional frequency spectrum, fabric defects were extracted by detecting abnormal value in two central spatial frequency spectrums. However, Fourier analysis is not suitable for detecting local defects. Because it is very hard to quantify the contribution of each spectral component of the infinite Fourier basis. (2) Through decomposing images at different scales into a hierarchy of localized sub-images, multi-scale wavelets representation can be applied for fabric defect detection [18]. In Kim et al. [43], fabric images were characterized with an adaptive wavelet basis by using discrete wavelet transforms. Defects were then detected by an Euclidean distance-based detector in the feature images. In Hu et al. [16], after eliminating normal fabric texture by zero-masking dominant frequency components of the testing image, wavelet shrinkage was utilized to heighten the defective area in the residual image. Although it is much easier to detect local defects through wavelet transform which consists of small waves of varying frequency and limited duration, its massive computational cost cannot be ignored. (3) Gabor transform is a kind of windowed Fourier transform. Due to its merits of optimal joint localization in spatial and frequency domains [11], 2-D Gabor transform becomes a popular technique for various applications, such as boundary detection [27], texture analysis [8], and palm vein recognition [13]. Consequently, owing to its small bandwidth in both spatial and frequency domains, Gabor transform is regarded as a promising method for fabric defect detection. Generally, the existing defect detection models based on Gabor transform can be divided into two categories: models based on a Gabor filter bank and models based on optimized Gabor filters.

Some researchers have proposed fabric inspection models based on a Gabor filter bank which consists of more than ten filters that essentially cover the frequency domain. In Kumar and Pang [20], a set of twenty-four Gabor filters was generated at four scales and six orientations to detect the possible defects which may appear on the fabric. This method is based on the idea of multi-resolution analysis. Features of defects were represented by fusing the outputs of all Gabor filters, parameters of which were predefined empirically. Although the implementation of this detection model is quite easy, filtering by a Gabor filter bank can generate a huge amount of data, which might cause a disturbance to texture discrimination problem [41]. Thereafter, Li et al. [22] applied feature selection on a predefined Gabor filter bank to build a more compact filter bank. The performance of this approach primarily depends on the parameter settings of the original Gabor filter bank. In Bissi et al. [3], Principal Component Analysis (PCA) has been performed on the outputs of a Gabor filter bank, in order to reduce the dimension of feature vectors. Afterwards, Euclidean norm of the local features was calculated to distinguish defective areas. It is reasonable to conclude that fabric defect detection approaches based on a Gabor filter bank have two main drawbacks: (1) they are usually of high computational cost, which is vital to the real-time inspection system; (2) without automatic parameter adjustment, the empirical parameters cannot well handle different situations of the defect detection problems. It is worth mentioning that fabric defects commonly lie in only two directions: horizontal and vertical, as woven fabrics are made up of warp and weft yarns. Hence, Gabor filters in these two directions will be efficient for solving the defect feature extracting problems. Furthermore, the selection of appropriate Gabor filter parameters is very crucial to the performance of the detection model. Therefore, to optimize the parameters of Gabor filters in horizontal and vertical respectively comes to the first incentive of this paper.

Some detection approaches based on optimized Gabor filters have also been developed in these years. These approaches usually employ only one or several Gabor filters, parameters of which are optimized towards specific objectives. In Bodnarova et al. [4], fabric defect detection was treated as the problem of segmenting a known non-defective texture from an unknown defective texture. Along four directions, Gabor filters were optimized in a semi-supervised mode. With the prior knowledge of defect-free fabric features, the optimization objective was to achieve Gabor filters which can generate high response to defect-free fabric areas. Mak and Peng [24] proposed a defect detection system based on a nonlinear network which is called Gabor wavelet network (GWN), since the transfer function is a Gabor wavelet function. Defect-free images were employed as the template images of GWN. Characteristic parameters of the defect-free texture were acquired by training the GWN to minimize an error function, and then were utilized to design the optimal parameters of the Gabor filters for fabric inspection. Similar to the previous researches, Mak et al. [25] also used a defect-free fabric sample as the template image to optimize Gabor filters at seven scales by genetic algorithm. In Hu [15], defect detection was addressed by adopting an elliptical ring Gabor filter, the parameters of which were optimized by a simulated annealing algorithm. Likewise, the template images were defect-free samples as well. It is noticed that in the researches above, Gabor filters are optimized in accordance with the features of defect-free fabrics. These optimal Gabor filters would be good at figuring the features of standard fabrics. However, these filters may not perform well in detecting subtle defects which have not significantly altered the spectral features of normal fabric. It will be much easier to discriminate normal and defective fabric textures, if features of the both two textures are employed in the Gabor filters optimization. Therefore, how to build the optimization model for Gabor filters by utilizing both features of defective and defect-free fabric samples, which can achieve excellent discrimination effect, becomes the second incentive of this paper.

The third incentive of this paper comes from the selection of optimization methods. In Tsa and Wu [39], the optimal combination of the Gabor filter parameters was acquired by exhaustive searching in its theoretical region. This method is extremely time consuming, which is not suitable for real-time operation. In Bodnarova et al. [4], the Gabor filters were optimized by sequential quadratic programming (SQP). SQP is a gradient-based optimization method, the optimization results of which mainly depends on the initial values of variables. In Mak and Peng [24], the training process of GWN was conducted by the Levenberg–Marquardt algorithm, which is also a gradient-based optimization algorithms. Hu [15] adopted simulated annealing (SA) algorithm in the Gabor filters optimization. SA is a kind of stochastic optimization algorithm. Compared with gradient-based optimization algorithm, SA has increased the probability of achieving the global optimal solution by accepting some worse solutions with an adaptive probability in the optimization. However, since only a single individual is employed in the optimization, the performance of this algorithm is not stable. Moreover, it costs amounts of computational time. Inspired by biological evolution, evolutionary algorithm (EA) is a kind of population-based metaheuristic optimization algorithm, which includes genetic algorithm (GA) [14], differential evolution (DE) [35,36], particle swarm optimization (PSO) [17], and so on. Superior to gradient-based optimization algorithms, EAs can greatly avoid being trapped in local optima for optimization problems. Furthermore, due to the population-based metaheuristic scheme, the optimization efficiency can be significantly increased. Among these EAs, DE has proven to be a reliable and powerful EA for global numerical optimization. Over the past decade, various DE variants have been proposed to handle complicated optimization problems in diverse application areas,