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Fabric defect inspection based on lattice segmentation and Gabor filtering

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ABSTRACT

Fabric defect inspection aims at detecting the defects presented on a patterned fabric surface to achieve high quality. However, visual inspection is challenging due to the diversity of the fabric patterns and defects. This paper presents an automatic defect inspection method which compares the similarities of semantic sub-images conformed to crystallographic groups called lattice. The lattices are automatically segmented based on morphological component analysis (MCA). The defect inspection is then formulated as a novel voting procedure depending on an ideal lattice artificially generated by investigating the distributions of responses given by convolving lattices with Gabor filters. The performance of the proposed method LSG (lattice segmentation assisted by Gabor filters) is evaluated on the databases of star- and box-pattern images. By comparing the resultant and ground-truth images, an overall detection rate of 0.975 is achieved, which is comparable with the state-of-the-art methods.

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1. Introduction

As one of the antique inventions of human beings [1], fabric evolves through human history from the hand-crafted woven textiles to modern electronic textiles [2] produced by machines. Although the means of fabric manufacture revolutionarily changed [1], the flaw on the fabric surface called defect still occurs due to the machine faults, yarn problem and other reasons. The loss of profit caused by defects can be up to 45–65% [3]. Fabric defect inspection (or detection) aims at controlling fabric quality by identifying and locating the defects. However, most inspection of fabric defects relies on human workers nowadays [4]. As a traditional way for identifying the defects, visual observation by human being can achieve the succession rate of 60–75% [5]. Contrastively, a state-of-the-art automated fabric inspection achieves accuracy higher than 90% [6]. The unstable detection accuracy and high labor cost drive the fabric manufacturers to automate defect inspection, but the automatic inspection is not easy to implement mainly due to the various fabric patterns and the diverse defects which could be categorized into more than 70 types [6]. Computer-vision based methods inspect the defects through analyzing the two-dimensional (2D) textures representing the fabric surfaces. The two-dimensional (2D) textures representing the fabric surfaces have been widely researched. One of the findings is any 2D textures can be generated using patterns conforming 17 rules (groups) named crystallographic or wallpaper groups [7]. These groups are represented by the small repeated pattern called lattice, and lattice itself can be further dissected to motifs. Fabric defect inspection methods are thus categorized as motif-based and non-motif-based [6]. Essentially, the two categories are classified based on whether a given method is built on the wallpaper-groups-based sub-image segmentation (WSS) according to the wallpaper groups. WSS methods attempt to automatically dissect the fabric image to sub-images like motif or lattice defined by wallpaper groups, while non-WSS methods segment sub-images based on theories different from wallpaper groups or completely do not work at the sub-image level.

Most of non-WSS algorithms are designed for the plain and twill fabrics categorized as p1 in wallpaper groups; a few have the capabilities to process other types [6]. The typical theories and morphologies of methods incapable of processing textures other than p1 group comprise auto correlation [8], co-occurrence matrix [9,10], mathematical morphology [8,10], fractal [11], Fourier transformation (FT) [12,13], wavelet transformation (WT) [9,14,15], autoregressive model (AR) [16], etc. Two approaches are reported in [8], one approach estimates the regularity of graphical element layout based on the auto-correlation version of a given fabric image, and the defects are identified as the outliers breaking the

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regularity. The reference frames for generating the auto-correlation results are mandatory for auto-correlation based methods. The other approach in [8] estimates the orientation of element layout and identifies the defects based on mathematical morphology. Co-occurrence-matrix-based method [9] decomposes a given image to sub-bands through wavelet transformation, and compute the feature values like entropy of co-occurrence matrices of the sub-images segmented from sub-bands. The defects are then identified using a Mahalanobis-distance classifier trained by defect-free samples. The method proposed in [10] segments the defects by combining the thresholding and morphological operations, then classifies the defects based on the features like energy and inertia of the co-occurrence matrix computed based on the given grayscale leather fabric image. This method not only identifies but also classifies the defects. Fractal method in [11] employs the box-counting method to evaluate the box dimensions which approximate the fractal dimensions defined for the theoretical fractal. The evaluated box dimensions are then used as feature values for measuring the similarities of sub-images covered by boxes. The fundamental theory of fractal methods serving for segmenting sub-images is completely different from WSS methods based on wallpaper groups. FT-based method in [12] finds the Fourier power spectrums of some defects concentrated at the center of spectrum space; hence a spread radius in spectrum space is chosen to filter the spectrums which result in an image of approximate uniform grayscale except the regions of defects. Thus, the defect inspection becomes a simple thresholding problem. The approach reported in [13] finds the Fourier power spectrums of some defects concentrated around the center of spectrum space. The distributions of spectrums within the central region of spectrum space are analyzed along horizontal and vertical directions. The defects are identified and classified according to the feature values computed based on the spectrum distribution. WT-based method in [15] divides the fabric image into non-overlapping sub-images, and then extracts feature values of each sub-image based on their wavelet coefficients obtained by an adaptive wavelet transformation. The wavelet filters are optimized by minimizing the loss function of the detection results. The approach in [14] considers the fabric images of oriented and non-oriented textures. Finding the defects in images of different types can be highlighted in the image reconstructions using different sub-bands of wavelet transform. Sub-band selection for reconstruction is based on the analyses of the wavelet coefficient energies, and the defects are identified by thresholding the reconstructed images. AR-based method in [16] arranges pixels of an image to a single row and scans the pixel sequentially, the gray value of pixel under scanning is compared with the ideal value predicted by the 1D autoregressive model w. r. t. the previously-scanned pixels. The model parameters are trained by minimizing the prediction error for defect-free samples. However, there are no statistical results in [16] for evaluating the performance. Although, the discussed approaches contribute some findings for detecting fabric defects and illustrate abundant elaborately-designed methods, these approaches are restricted to fabric of p1 group only, which severely limits their applications. Hence, the *first motivation* of this paper is to design a method capable of processing fabric textures besides p1 group.

On the other hand, non-WSS methods capable of processing textures besides p1 group comprise wavelet-pre-processed golden image subtraction (WGIS) [17], co-occurrence matrix (CM) [18], Bollinger bands (BB) [19], regular bands (RB) [20], image decomposition (ID) [21], Elo rating method (ER) [4], etc. Although WGIS, BB, RB and ER can handle wallpaper groups besides p1, some manually-chosen graphical elements are always presented one way or another. For instance, WGIS and MB use not only the size but also the texture of the element; BB, RB and ER require the sizes to be predefined. The prerequisite knowledge for defect inspection accuracy is hard to obtain for the real-world applications because of the diversity of the defects, e.g., there are more than 70 types of fabric defects [6]. This inherent limitation restricts the applications of the methods. There are methods avoiding the requirement of the prerequisite knowledge about the graphical elements like ID. As one of methods without the prerequisite knowledge, ID is designed based on a technique called image decomposition of capability to separate texture and cartoon (non-texture graphics like edges) for a given image. The image decomposition method adapted by ID is built on the model involving blurry and missing pixels [22]. This model consists of two parameters τ and μ. For a defective fabric image, a defect-free image $\boldsymbol{I}^*$ is chosen and decomposed to cartoon $\boldsymbol{u}(\tau, \mu)$ and texture $\boldsymbol{v}(\tau, \mu)$. ID attempts to find the pair of (τ^*, μ^*) maximizing the Pearson's correlation coefficient of $\boldsymbol{I}^*$ and $\boldsymbol{v}(\tau, \mu)$, $\boldsymbol{u}(\tau^*, \mu^*)$ is labeled as defects. Theoretically, all possible combinations of $\tau > 0$ and $\mu > 0$ should be estimated, ID only searched the ranges $0 < \tau < 0.8$ and $0 < \mu < 4$. Even for these restricted ranges, the image decomposition has to be repeatedly conducted for many times, which is computationally prohibitive. Therefore, the *second motivation* of this paper is to adapting an image decomposition algorithm for avoiding the requirement of the prerequisite knowledge about the graphical elements.

There are a few WSS methods. The representatives are motif-based method (MB) [7] and its improved version [23] which are capable of processing textures other than p1 group [6]. MB is the first WSS method presented in the literatures [6]. MB and its inheritors depend on Liu et al.'s lattice extraction model [24] for automatically segmenting motifs. Since Liu et al.'s method is designed on the basis of wallpaper groups, the segmented sub-image is guaranteed to be consistent with the motif. As a famous lattice segmentation method, [24] is widely used in many applications [25,26]. However, the main issue of this method is that the number of peaks cannot be automatically determined [25,26]. In addition, MB has another severe limitation due to its design. MB depends on the energy of moving subtraction $K_{s,\,r}$ which requires at least two lattices. Specially, for MB and its successor, a given image of known category in wallpaper group is preprocessed by Liu et al.'s method, and the motifs are extracted based on the category. Suppose there are at least two motifs $\boldsymbol{M}^s$ and $\boldsymbol{M}^r$ employed to generate sets of circular-shifted matrices $\boldsymbol{M}^r_{ij}$ and $\boldsymbol{M}^s_{ij}$, $i = 1, 2, \ \ldots \ , m$ and $j = 1, 2, \ldots, \ n$, then $K_{s,\,r}$ is defined as below:

$$K_{s,r} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left\| \boldsymbol{M}^r_{ij} - \boldsymbol{M}^s_{ij} \right\| \Big/ (mn)^2. \tag{2}$$

Wherein $\|\boldsymbol{M} - \boldsymbol{N}\| = \sum_{k=1}^{K} \sum_{l=1}^{L} |m_{kl} - n_{kl}|$ for matrices $\boldsymbol{M}$ and $\boldsymbol{N}$. Ranges of minimums and maximums of $K_{s,\,r}$ and its variance energy $V_{s,\,r}$ for defect-free images are estimated, respectively. For a test image, any motifs with $K_{s,\,r}$ and $V_{s,\,r}$ values beyond the ranges are labeled as defective. Hence, the *third motivation* of this paper is to develop a fully-automatic lattice segmentation method with and a corresponding feature extraction method without requirement of number of motifs or lattices.

In this paper, a novel method based on lattice segmentation assisted with Gabor filter (LSG) for automatically segmenting lattice and identifying fabric defects is proposed. The essential idea is to represent a given fabric image by semantic sub-images called lattices and identify the defects by extracting and comparing the features for each lattice using a small Gabor filter bank. The proposed lattice segmentation method is based on the coarse cartoon component of the fabric image generated by only a single iteration of Morphological Component Analysis (MCA) [27]. The segmentation is formulated as a clustering problem of the pixels corresponding to gaps between neighboring patterns, thus any texture images of high-contrast patterns extended orthogonally can be theoretically segmented to lattices. This generality may be further improved with contrast enhancement and calibration. Un-

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