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Fabric defect detection systems and methods—A systematic literature review

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A B S T R A C T

This paper presents a comprehensive literature review of fabric defect detection methods First, it briefly explains basic image acquisition system components such as camera and lens. Defect detection methods are categorized into seven classes as structural, statistical, spectral, model-based, learning, hybrid and comparison studies. These methods are evaluated according to such criteria as the accuracy, the computational cost, reliability, rotating/scaling invariant, online/offline ability to operate and noise sensitivity. Strengths and weaknesses of each approach are comparatively highlighted. In addition, the availability of utilizing methods for weaving and knitting in machines is investigated. The available review studies do not provide sufficient information about fabric defect detection systems for readers engaged in research in the area of textile and computer vision. A set of examination for efficient establishment of image acquisition system are added. In particular, lens and light source selection are mathematically expressed.

1. Introduction

In textile industry, fabric production is usually done on weaving and knitting machines. Fabric is produced from textile fibers. Textile fibers are generally manufactured with natural element such as cotton. A fabric defect corresponds to a flaw on the manufactured fabric surface. In particular, fabric defects result from processes such as machine defects, faulty yarns, machine spoils and extreme stretching. More than 70 kinds of fabric defect are defined by the textile industry [1]. Most of defects occur either in the direction of motion or perpendicular to it. In terms of quality standards, the defects on the fabric surface are categorized into two: surface color change and local texture irregularity [2]. Six common fabric defects are shown in Fig. 1. Float (Fig. 1(a)) is caused by breaking of needles, weft curling (Fig. 1(b)) is caused by inserting a highly twisted weft thread, and a slub (Fig. 1(c)) can be caused by thick places in the yarn or by fly waste being spun in yarn during the spinning process. Hole (Fig. 1(d)) is a mechanical fault caused by a broken machine part. Stitching (Fig. 1(e)) is a common fabric defect. This defect is a result of any undesired motion of the main or auxiliary loom mechanisms. Rust stains (Fig. 1(f)) are caused by lubricants and rust. Not only do such serious defects make the sale of the fabric impossible, they also lead to the loss of revenues [3]. A fabric defect detection system improves the product quality. As a result, automated fabric defect detection systems to manufacture the high quality of textile products are in increasing demand. This automated system is done by identifying the faults in fabric surface using the image and video processing techniques.

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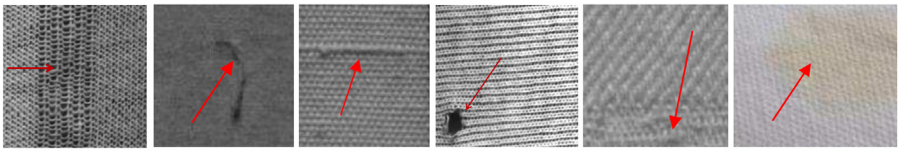

Fig. 1. Example defects namely (a) needle breaking, (b) weft curling, (c) slub, (d) hole, (e) stitching (f) rust stains. (Arrows point to defective regions.).

Fabric defect detection is the determination process of the location, type and size of the defects found on the fabric surface. Generally, human inspection is used for fabric defect detection. It provides instant correction of small defects, but human inspection cannot detect errors due to carelessness, optical illusion and small defects [3–5]. However, human inspection fails on detection defects in terms of accuracy, consistency and efficiency, as workers are subject to boredom and thus inaccurate, uncertain inspection results are often occurred. Thus, automated fabric inspection becomes an efficient method forward to improve fabric quality [6,7].

In automated inspection, defect detection is carried out during the production process. In real-time inspection, these systems detect the defect and are able to stop the production process just when the defect has occurred. Automated systems are able to provide detailed information about the defect to the operator [8–10]. Components of automated defect detection systems are detailed in the next section. Recently, Ngan et al. [7] reviewed 139 papers for fabric defect detection. They performed a more comprehensive classification of approaches and split them into seven basic groups. Moreover, they categorized as motif-based and non-motif based methods. Yet, the majority of reviewed papers are related to woven fabric defects. Therefore, circular knitting fabric defects were not comprehensively considered in their paper. On the other hand, no informative explanation about the components of image acquisition system was presented. A similar review paper about fabric inspection was previously published by Mahajan et al. [2]. The current defect detection methods were divided into three categories: statistical, spectral and model-based. The main problem of this paper was that it was focused on the uniform fabric textures, but some kinds of fabric have a non-uniform textures. The other problem of [2] was similar to previous review approach [7] that no information about the image acquisition system was given. In this paper, the state-of-the-art fabric defect detection methods in structural, statistical, spectral, model-based, learning, hybrid and comparison approaches, which have satisfactory results are given. The main contributions of our paper are as follows: It presents a more comprehensive categorization of approaches of seven classes (i.e., structural, statistical, spectral, model-based, learning, hybrid and comparison). It also presents a qualitative analysis for each chosen method. Classification accuracy, strengths and weaknesses, utilizable in weaving and knitting fabrics are given for each method. In order to select the components of image acquisition system, it provides the comparative analysis.

2. Fabric defect detection system components

2.1. Camera selection

On-loom fabric image acquisition has some difficulties to acquiring high-quality images. One of the difficulties is the camera selection. Generally, two types of cameras are used for fabric defect detection: area scan and line scan cameras. Line scan camera can obtain images from the fabric surface area at high speeds in the form of lines. Line scan camera must be synchronized to the moving fabric by means of encoder. Camera-encoder interface application is utilized to obtain the true movement direction of the manufactured fabric. This interface provides accurate image-line triggering for line scan camera. Area scan camera may obtain at a more reduced speed, but it acquires the blurred fabric images. In Fig. 2, images obtained from different fabrics captured through area scan camera are shown. In the first column shows the stabile images and the second column shows the moving images. If looked carefully, image of the moving fabric is obtained too blurred to do any transactions on it.

To eliminate the blur in the images obtained by area scan camera, line scan cameras are preferred in the analysis of high-speed objects. Today, line speed cameras with 140 kHz (approximately 140,000 lines in 1 s) can be produced [11]. In Fig. 3, the data package obtained in 1 s from a line scan camera with the rate of 140 kHz, and how these data packages are converted into frames are shown.

As a result, the fact that area scan camera should be used in the analysis of static fabric. In addition, line scan camera should be used in the analysis of moving fabric.

2.2. Lens selection

After the selection of the suitable camera, an appropriate selection of lens is needed. The area to see and field of view with a camera depends on the lens used. Therefore, the most right lens should be chosen taking such values as the working distance, field of view and the size of the sensor. Due to the fact that the sizes of the picture to be formed, its shape and

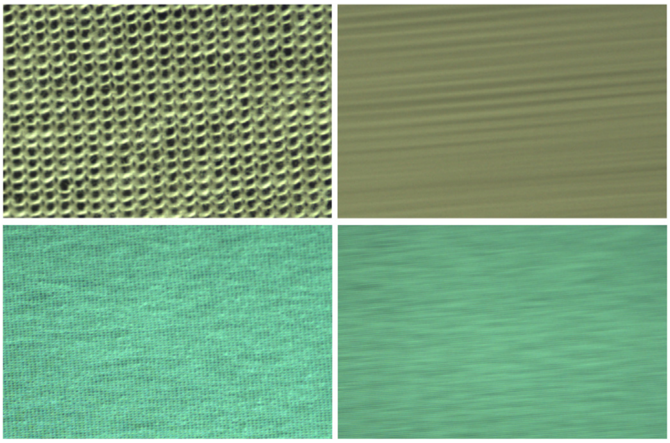

Fig. 2. The fabric images obtained by area scan camera (First row: 2518 × 1900 resolution. Second row: 780 × 640 resolution. First column: The machine is stationary. Second column: The machine is running.).

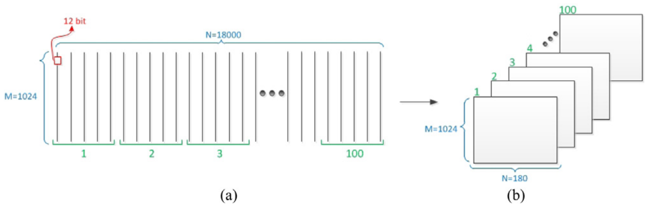

Fig. 3. (a) The size of the data obtained in a second with line scan camera, (b) transformed of '(a)' data into video.

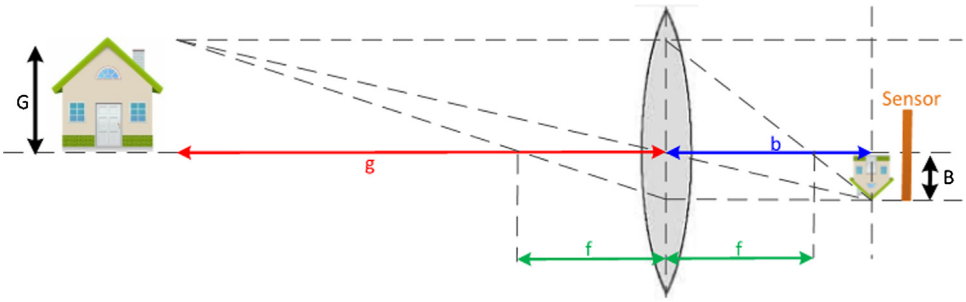

Fig. 4. A schematic diagram of the relationship between image and object distance (b and g, respectively) and lens focal length (f).

clarity are directly related to lens selection. For this reason, focal length *f* value should be calculated. *f* value can be calculated by the following formula:

$$f = \frac{\mathrm{B}}{\mathrm{G}} \times \mathrm{g} \tag{1}$$

where *B* and *G* are the image size and object size, respectively. *b* and *g* are the image distance and object distance, respectively. Fig. 4 presents the geometric relationships between image and object distance (*b*and *g*, respectively) and lens focal length (*f*). Each lens has Fixed Focal Length (FFL) values. Any lenses between the calculated value of the *f* and the FFL values of lenses equalizing $f - 2 \leq FFL \leq f + 2$ can be selected. For the selection of the lens, a web-based application can be accessed from [12]. The above formulation formally defines a measure of focal length that is related to the vague distance between object and camera. Researches should regard magnification factor for optimal image quality. In the industrial image processing applications, magnification factors >1:10 (sensor size: object size) are required.

2.3. Light selection

Lighting is a fundamental problem for many machine vision and image acquisition systems. Four different lighting schemes are used for automatic fabric control systems [3]. These are the front, back, fiber-optic and structural lighting techniques. The front lighting technique is generally used for examining the thick fabrics and is positioned at the same loca-

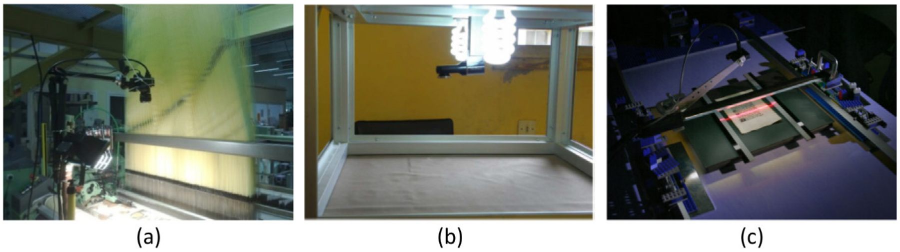

Fig. 5. (a) Halogen light source [13], (b) fluorescent light source [14], (c) linear light source [15].

Fig. 6. Frame grabbers that have different port number.

tion with the camera on the front of the fabric. As for the backlighting technique, it is used to eliminate the effects of ghosting in the semi-transparent fabric structures. When compared with the front side lighting, the line light source located at the back of the fabric allows us to obtain images with more appropriate contrast. Fiber optic lighting type is not economical for the images of fabric larger than 1.82m. In order to be able to distinguish between defected and defect-free fabric images, infrared light and high frame rate camera are used in structural lighting systems. In the literature studies, fluorescent lamps, halogen lighting, and different designs of Light Emitting Diodes (LED) light sources are in general used. Some light source prototypes are shown in Fig. 5.

The width of light is very important to capture the quality images. The following formula can be used to select an optimal width of the light:

$$\mathrm{Lightwidth}\,(\mathrm{mm}) = \mathrm{illuminatedarea} + (2 * \mathrm{cameraworkingdistance}) \tag{2}$$

In electromagnetic spectrum, the human eye can see the radiations between 400 − 700 nm wavelength range. LED lighting provides lighting in a quality close to the human eye. For this reason, in fabric control systems developed in recent years, in order to achieve effective and successful machine vision, line LED lighting is preferred. For effective use of LED lighting, the width of the light must be selected according to the formula given above.

2.4. Frame grabber

Frame grabbers are used as an element of data transfer between the camera and the data processing unit. In order to transfer from camera to the data processing unit, each data must be stored and delivered quickly. As high-speed line cameras are needed for fabric defects detection process, it is essential to use the frame grabbers. Otherwise, there will be losses in camera data produced sequentially. Multiple camera data can be transferred to the computer at the same time owing to frame grabber. In Fig. 6, frame grabbers with different numbers of ports are shown.

3. Fabric defect detection approaches

In this paper, fabric defect detection methods are categorized into seven classes: structural, statistical, spectral, model-based, learning, hybrid and comparison.

3.1. Structural approaches

Structural approaches consider texture as a composition of textural primitives. Texture analysis is performed by obtaining the texture features and inferring their replacement rules [2]. According to this approach, the overall texture of the fabric pattern can be achieved with the composition of simple texture structures. Structural texture analysis contains two sequential stages [5]: i)detection of basic fabric textures. ii) modeling of the overall fabric texture pattern. Abouelela et al. [16] performed the detection of structural defects. Thus, the reliability of the structural approaches is low. Structural approaches are only reliable in segmenting fabric defects from texture whose pattern is very regular [17].

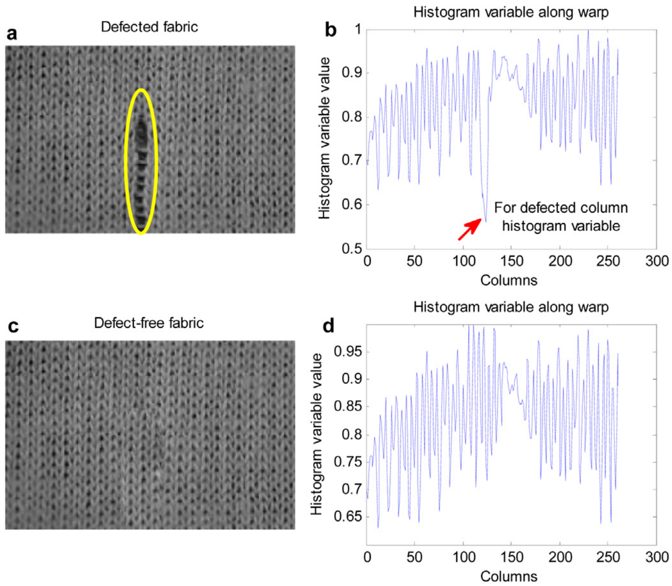

Fig. 7. (a) Defected fabric image, (b) the values of histogram variable $P_{warp}(x)$ of any row in defected fabric, (c) defect-free fabric image, (d) the values of histogram variable $P_{weft}(y)$ of any row in defect-free fabric.

3.2. Statistical approaches

Statistical approaches use first-order statistics and second-order statistics to extract textural features in texture classification. Most of the methods used in this approach include co- occurrence matrix, histogram features, auto-correlation function and mathematical morphology approaches. Also, there exist other statistical approaches such as cross-correlation, statistical moments, edge detection and neural network methods in literature reviews.

3.2.1. Histogram-based approaches

Histogram contains the basic statistical data of gray-level pixel distribution of the image [18]. Histogram variables in the warp and weft directions of a gray level $I(x, y)$ image with MxN dimensions are obtained as follows:

$$P_{warp}(x) = \frac{1}{N}\sum_{y} I(x, y) \quad (3)$$

$$P_{weft}(y) = \frac{1}{M}\sum_{x} I(x, y) \quad (4)$$

For defected and defect-free fabric images, histogram variables $P_{warp}(x)$ and $P_{weft}(y)$ are shown in Fig. 7. As it is shown in Fig. 7, warp-knitted and weft-knitted fabrics are efficiently analyzed in terms of fabric defects. The defective area in the fabric image of Fig. 7 starts at warp coordinate 122, and end up with warp coordinate 138.

The most common histogram properties are mean, standard deviation, variance, and median. Despite their simplicity, histogram techniques are used in various applications due to features such as lower computational cost [19,20]. In recent years, Ng [21] histogram separation technique developed. In [22–24] studies, by examining the histogram differences of defected and defect-free fabric images, defect detection was performed. Simplicity of application and high computational speed are positive properties of the histogram-based methods. However, the reliability of these methods is low.

3.2.2. Co-occurrence matrix-based approaches

These methods provide the characterization of properties of texture by measuring dependencies between color intensities. The distribution of gradient orientations in particular offset on the fabric image is expressed [25,26]. The combinations of gradient orientations are used to express the texture of the fabric.

To determine the fabric defect in woven fabrics, Bodnarova et al. [27] used the spatial gray level dependence matrices for improved texture description. They computed energy, entropy, inverse difference moment, correlation and contrast. Hanbay et al. [28] obtained gray level co-occurrence matrices for different offset and angle values and classified them with artificial neural networks. In another study carried out on the motionless fabric images, 90.78% success was achieved in the detection of fabric defects using the method of sub-band gray level co-occurrence matrix [29]. In this study, such characteristics of co-occurrence matrix as entropy, contrast, angular momentum speed and inverse difference momentum were used. To detect defects in knitted fabrics the defect detection process was carried out [30]. In [31], contrast, homogeneity, energy and correlation properties of co-occurrence matrix were obtained and online fabric defect detection system was performed.

The disadvantage of this study is the use of a uniform type of fabric. The desired success rate cannot be achieved in different types of fabrics.

Co-occurrence matrix approachis negatively affected by the noise and filtering stages are needed. There are two main weak point of co-occurrence matrix approach: (1) it has poor performance in high-resolution images. So, the accuracy ratio can be increased by using the wavelet transform method, (2) it has high computational cost.

3.2.3. Auto-correlation-based approaches

It is a method of examining the repeated structures of fabric images [32–34]. If the image has a defect, because of the fact that the regular structure will deteriorate, saddle or valley views come up in response to auto-correlation function [35].

Zhang and Bresee [32] combined autocorrelation functions and morphological operators to detect knot and slub defects. This method is quite robust against noise and lighting changes in structure. In this respect, it is superior to statistical methods. In addition, the classification accuracy rate on certain types of fabric images is very high when compared with morphological methods [32]. However, high calculation time is a considerable disadvantage. In [34] study, classification of fabric defects was carried out by using this method.

3.2.4. Mathematical morphology-based approaches

Mathematical morphology is feature extraction method based on preliminary information about the geometry of the object [36]. A morphological operation is defined as the examination of image set by using a small cluster called configuration element. The basic operations of mathematical morphology are expansion, erosion, opening and closing. The expansion, erosion, opening and closing operations of a A set with a B configuration element can be expressed as follows:

$$\text{Expansion}: A \oplus B = \left\{ x | (B_x) \cap A \neq \phi \right\} \tag{8}$$

$$\text{Erosion}: A \ominus B = \left\{ x | (B_x) \subseteq A \right\} \tag{9}$$

$$\text{Opening}: A \circ B = \left(A \Theta B \right) \oplus B \tag{10}$$

$$\text{Closing}: A \cdot B = (A \oplus B) \Theta B \tag{11}$$

It is used in conjunction with correlation function or co-occurrence matrix. The level of classification accuracy rate of this hybrid system achieves 96.7% [37]. In [38,39], a method which detects the location of fabric defects by using improved morphological erosion operator was developed. However, the accuracy rate of the method was not given. In a real-time system application of defect detection cooperated with an optimal morphological filter that runs on certain types of different fabric images, the accuracy rate was reached as 97.4% [40]. In another study, the fabric defects were detected using the correlation, wavelet transform and morphology methods jointly [41,42]. However, the size and location of fabric defects can be detected effectively and quickly by using the appropriate structural element.

3.3. Spectral approaches

Both spatial and frequency domain information are necessary for fabric defect detection. Especially, frequency domain information is essential for identification of presence of defect in fabric surface. In addition, spatial domain information is required for identify the location of the fabric defect. A large number of studies conducted on fabric defect detection focuses on spectral approaches. Spectral approaches intend primarily to remove the basics of image texture, and then generalize the basics of this texture with the spatial layout rules. These approaches require a high degree of periodicity. That fabric yarns or patterns are periodic structures provides the use of spectral approaches. However, it is not suitable to use spectral approaches for fabrics containing random texture. As subtitles of spectral approaches, the wavelet transform, Fourier transform, Gabor transform and filtering methods will be examined.

3.3.1. Wavelet transform

Wavelet transform is a signal analysis technique which was developed as an alternative of Fourier transforms to optimize the frequency-dependent temporary resolutions [43,44]. In a recent study, for the removal of the properties of the yarn images, statistical measurements and discrete wavelet transform are jointly used [38]. In [45], defect detection in the fabric images of 1 m width is made using the method of the wavelet transform on a real-time fabric manufacturing machine. In a study using adaptive wavelet, eight different types of defects are identified in the images [46]. Thanks to multi-scale and adaptive usage, the defected area is enabled to be realized through increasing the difference between the defect and background of the fabric. In [47], to find defects in the knitting fabrics, *Dempster-Shafer decision theory* and a method based on wavelet transform are developed. In this study, three main wavelets best characterizing those examined types of defects are defined. Karlekar et al. [42] developed wavelet filter method for modeling of fabric texture and defect detection. They successfully combined morphological operators and wavelet transform to detect horizontal, vertical and diagonal line defects. Kang et al. [48] studied the wavelet transform and neural network classification on the fabric defect detection. Sakhare et al. [49] developed spectral domain method for fabric defect detection. To detect fabric defect, they used various block processing algorithms of Fourier transform, Wavelet and Gabor filter. In the wavelet transform stage, horizontal and vertical transformed images were calculated. Wavelet sub-band images were divided into non-overlapping

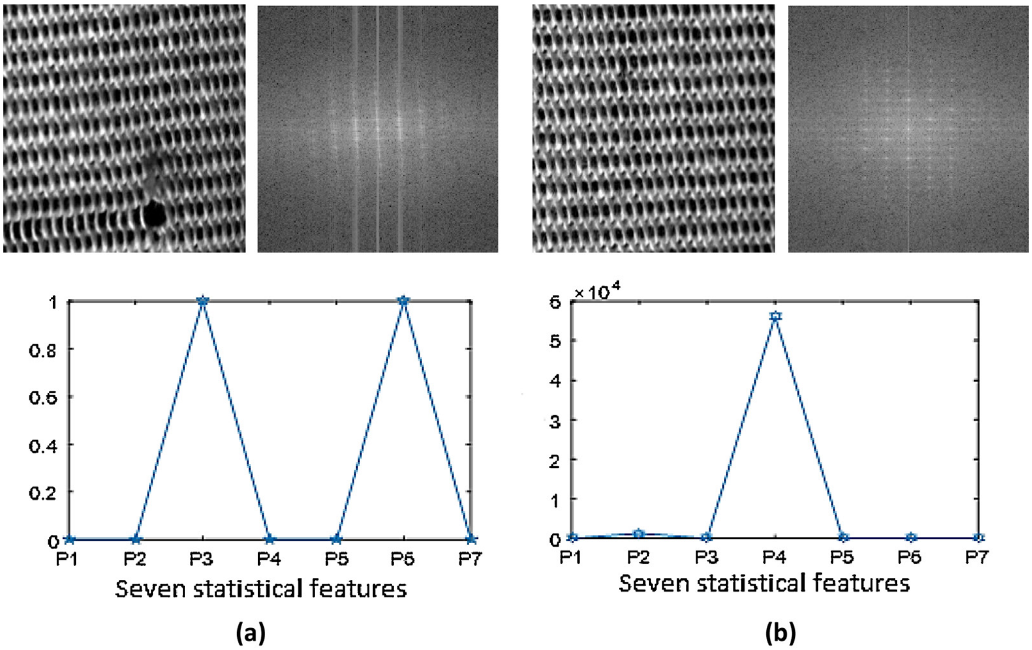

Fig. 8. Seven statistical features extracted from Fourier transform: (a) for defective fabric image (b) for defect-free fabric image [57].

windows. Standard deviation of each window was calculated. By a decision rule, fabric images were classified. In the design of wavelet frameworks used, discriminative feature extraction method [50] is used. The success rate of wavelet transform technique is high. However, each operation can work only for a certain type of fabric and the specific defect classes. There is no clear information in articles detecting certain types of defect types indicating why main wavelet types are preferred. However, wavelet transform technique is suitable for real-time applications and knitting machine inspection due to its suitability of computation time.

3.3.2. Fourier transform-based approaches

Fourier transform is an analysis technique that enables a detailed analysis carrying signals from the time domain to the frequency domain. In image processing, this technique and texture images are characterized in terms of frequency components. The size of fabric image does not change during transformation.

Malek [13] performed real-time detection of defects using Fourier transform. In the developed approach, attributes of static defective fabric images were obtained through cross-correlation and fast Fourier transforms (FFT) techniques. In the next step, real-time fabric defect detection was developed with a system placed on the weaving machine using line scan camera. In another study, to classify four fabric defects common in plain fabrics, the central spatial frequency spectrum obtained by Fourier transformation was used [51]. In this study, two dimensional central spatial frequencies were used instead of three-dimensional frequency spectrum obtained with the Fourier technique.

Tsai et al. [52] proposed a global approach for the automatic inspection of fabric defects. The proposed approach does not rely on local features of fabric textures. They developed a global image restoration scheme using the Fourier transform. In addition, a statistical scheme was used to perform discriminating between defects and homogeneous line patterns. In another study, the realities of fabric images were evaluated using the Fourier spectrum obtained by Fourier transformation [53]. In this study, histogram equalization process was used and spectral sizes of the images and the phases were calculated and compared. An optical method using Fourier transformation and spatial filtering is used to reveal defects in textured materials in real time. Ciamberlini et al. [54], on the other hand have used Fourier transformation and spatial filtering to detect defects in fabric materials.

Also, in [55,56] references, although it is a claim that it was successful in detecting defect with the Fourier transform, their reliability is exactly unknown. Recently, Hanbay et al. [57] applied Fourier transform to detect the knitting fabric defects on a circular knitting machine. Textural features of knitting fabric images are calculated based on Fourier transform. These textural features are seven and are calculated from the horizontal and vertical directions of Fourier frequency spectrum. The proposed method was tested on circular knitting machine under industrial conditions. Detection success rates of this method ranged from 86% to 100%. Fig. 8 shows the calculated seven statistical features. Fourier transform is very strong in monitoring the moving fabric images in real-time systems. It is because of the fact that since the size of the Fourier spectrum is of absolute magnitude, *X* and *Y* direction movements of the fabric do not change the value of Fourier spectrum. So, the Fourier spectrum is only affected by changes in the structure of the fabric. Because of this advantage of it, this process is suitable for usage in real-time detecting fabric defect. It is also possible to make real-time applications with fast Fourier transform for the control of high-speed produced fabrics in knitting machines.

3.3.3. Gabor transform-based approaches

Gabor filters used in fabric defect detection are a function of the Gaussian distribution obtained by a complex sinusoidal. Gabor filters are used to make texture analyzes in both spatial and frequency domain. These filters, which can be customized with different scale and angle values according to the texture structure, are extensively used in detecting fabric defects. Tong et al. [58] developed a defect detection model using optimized Gabor filters. The proposed method uses composite differential evolution (CoDE) to optimize the parameters of Gabor filters. In a system developed for making production control on weaving loom, the frequency and direction data obtained from a total of 16 Gabor filter convolutions with 4 different angles and scales were calculated, and this data was used in fabric control [59]. The main weakness of these two methods is their being studied on a limited number of samples. In a recent study, 360 fabric images were classified using the Gabor transform and Gaussian function in a hybrid structure [60]. Zhou and Yang [61] developed the criteria of choosing the optimal Gabor filter. Then, they used the optimal Gabor filter to detect defections for glass fiber clothes.

Escofet et al. [62] proposed a set of multi-orientation and multi-scale Gabor filters to inspect fabric surface defects. In [63] a new hybrid method for automated defect detection implementation was developed using co-occurrence matrix and also was compared it with Gabor filter method. A bank of Gabor filter with different orientations and scales was produced and fabric images were filtered with convolution mask. Another approach based on the multiple Gabor filters and Kernel Principal Component Analysis (KPCA) was proposed to detect uniform and structured fabric defects [64]. In the proposed method, fabric images are firstly filtered by various Gabor filters with four orientations and six scales to compute feature vectors. The high-dimension feature vectors were reduced by using KPCA. The similarity matrix was computed by Euclidean norm and segmented with OTSU method. This method obtained a high true detection rate for online fabric inspection successfully. Gabor transform provides both spatial and spatial-frequency representation. It can extract the outstanding features of all defects. However, since the Gabor filters are rotation-based filters, they are vulnerable to the rotational transforms of the images.

3.4. Model-based approaches

Model-based defect detection approaches base on the construction of an image model. With the help of the model built, identification of the texture as well as texture synthesis is carried out. This technique is suitable for fabric images which may have surface changes due to defects such as yarn breakage and needle breakage [65]. Parameters of the model to be used are important to capture the necessary details in texture. The advantage of model-based defect detection approaches is that they can produce fabric textures that can match the observed fabric textures. In this study, the most commonly used Autoregressive model and Gauss Markov Random Field techniques are examined.

3.4.1. Autoregressive (AR) model

This model is used to express the degree of linear dependence between the different pixels of an image containing texture. The reason why this technique is widely used is because of the fact that it requires only the solution of linear equation systems. Compared with non-linear systems of equations, this technique has lower computational time. For real time fabric inspection, one-dimensional AR model has been used on digital signal processing module of TMS320C5X model [66]. Also, though few studies have been made for fabric control and image segmentation [67,68], no reliable and of the high-to-date studies have been made in recent years. Additionally, the studies analyzed have been made on limited samples and the accuracy rates have been also disclosed [65].

3.4.2. Gaussian markov random field model

Pixel points in fabric images are dependent on each other unless they include noise. Markov Random Fields (MRA) is sensitive models which use this dependence. In these models, the relationships between pixels and abrupt changes are measured by calculating the density value of each pixel on a local area. This method is used in many areas such as segmentation, classification and feature extraction [69,70]. Cohen et al. [71] used the MRA to model the textured image of a defect-free fabric image. In the developed method, fabric images were modeled by MRA models which were shown to extract well the visual textural information of the many fabric types. Ozdemir and Ercel [72] performed defect detection of textile fabrics through Karhunen-Loeve (KL) transform and MRA models.

3.5. Learning approach

Tsang et al. [73] developed a novel Elo rating (ER) approach to obtain defect detection in the spirit of sportsmanship. The ER method was carried out well in the dot- and star-patterned fabrics. The proposed method achieved 96.89% accuracy for dot-patterned fabrics. Kumar [74] carried out defect detection on the feedback ANN through a method based on regional relations of the pixels in raw textile images by obtaining their texture features. Yapi et al. [75] proposed a novel method that uses supervised learning to classify textile textures in defect and non-defect classes. They utilized the Bayes classifier (BC) to learn signatures of defected and non-defected classes. In the second phase, defects are detected on new images

Table 1
Strengths & weaknesses of fabric defect detection of statistical approach methods for well-known fabric and defect types.

Methods	Strengths	Weaknesses
Gray level Co-occurrence matrix	• Extracting spatial relationship of pixels with different 14 statistical computations • High accuracy rate	• Computationally expensive for the demands of a real-time defect inspection system. • Difficult to determine the optimal displacement vector • Require feature selection procedure • Dependent on the rotation and scaling
Histogram methods	• Computational simplicity. • Invariant to translation and rotation • Ideal for use in application to tonality discrimination	• Sensitive to noise • Low detection rate in the error detection of non-regular textures
Auto-correlation function	• Durable to noisy and illumination changes • Computing complexity is fairly low. • Perform a direct and accurate measure of similarity between two images • Suitable for plain weave fabrics	• Computational intensive for real time applications and large size images • This function can be sensitive to noise interference • Unsuitable for random fabric textures
Mathematical morphology	• Efficient on aperiodic image defects. • Geometric representation of texture images • It has computational simplicity • Very suitable for random or natural textures • Utilizable in weaving and knitting machines to detect and identify defects	• The morphological operations are only implemented on non-periodic fabric defects.

using the trained BC and an appropriate decomposition of images into blocks. In order to understand the effect of plasma processes and fabric properties on the surface of moist woven fabrics, a modeling study using ANN was conducted [76]. In the study, by conducting fuzzy logic-based feature selection, classification was made with the aid of ANN through removing of fourteen features to express fabric, and two to describe the plasma. Semnani and Vadood [77] developed an intelligent system based on ANN, which calculates the quality of the external appearance of knitted fabrics. They provided the best way to optimize the network by optimizing ANN with Genetic Algorithm. In this study, the correlation coefficient between ANN and observer was found to be 0.972. Wong et al. [78], through the direct thresholding model based on wavelet transform technique, developed a method that carry out defect detection and classification in fabric images having five different types of seam defects. In their study, after reduction process of the noise, defective pixels were segmented by calculating wavelet transform of the image. Shi et al. [79] used ANN for the segmentation of defects of fabric images obtained from the databases of line scan camera with 2048 sensor array, and TILDA [80] fabric. They made segmentation by using six statistical and four contrast parameters obtained from images as ANN input. Eldessouki and Hassan developed the objective pilling classification system of the fabric images using an adaptive neuro-fuzzy system (ANFIS) [81]. They use basic textural features extracted from the fabric images to obtain better distinctive features of the fabric surface. Furthermore, there are fabric defect detection studies made through such classifiers as the Support Vector Machines (SVM) [82]. Finally, Kumbhar et al. [83] presented a comprehensive survey on fabric defect detection methods. They particularly analyzed the SVM and linear classifier for fabric defect detection. However, thanks to the principle of parallel operation, ANN is considered to be heavily used in the future fabric defect detection systems. Deep neural networks (DNNs) have demonstrated excellent performance on texture classification. Especially, convolutional neural networks (CNNSs) have attracted much attention in many fields such as object detection and object classification. To our knowledge, there is little works which uses raw fabric image as an input in deep learning-based classification, but DNNs will become more popular in defect detection. For example, Seker et al. [84] developed a method based on deep learning and applied to fabric defect detection. They used autoencoder model as deep learning algorithm. The method achieved accuracies of 88%. Li et al. [85] were categorized into defect-free and defective categories by using Fisher criterion-based stacked denoising autoencoders (FCSDA). To deal with patterned fabric defects, fabric images are divided into patches of the same size. Then, these samples were used to train FCSDA. Finally, test patches were classified by using FCSDA into defective and defect-free classes. Experimental results showed that the FCSDA method could obtain the superior results on complex jacquard warp-knitted fabric. The classification accuracies of the FCSDA method ranged from 95.20% to 99.47% [85].

Table 2
Strengths & weaknesses of fabric defect detection of spectral approach methods for well-known fabric and defect types.

Methods	Strengths	Weaknesses
Wavelet transform	• Provides multi-scale image analysis • Enables to identify different defect types with different mother wavelets • Provides high accuracy rate • Textural feature extraction and possibility of direct thresholding • It can be used for noise reduction • Provides a high accuracy rate • Efficiently compresses the image with little loss of information • Utilizable in weaving and knitting machines to detect and identify defects	• In adaptive use, high computational cost • It suffers from either image components interference or features correlations between the scales
Fourier transform	• Spatial frequency spectrum is invariant to shift, rotation and scaling • Fabric images are characterized in the frequency domain • Fast computation and easy application • ·Suitable in the detection of global and local defects • FFT has a convenient calculation time ($2N\log_2 N$) • Utilizable in weaving and knitting machines to detect and identify defects	• Unable to detect random patterned fabric texture • Not working well for defect detection in random textures • It is not able to localize the defective regions in the spatial domain
Gabor transform	• Offers optimal defect detection for both spatial and frequency domain • Thanks to the different scales, offers high-dimensional feature space • An adaptive filter selection method is implemented to reduce the computational complexity • Perfect detection rates for defects on the edges and hole • Utilizable in weaving and knitting machines to detect and identify defects	• The choice of optimal filter parameters is quite difficult • It is not invariant to rotation • Intensive computation
Filtering approach	• Intensive use in the texton-based methods	• Intensive computation • The choice of optimal filter parameters is quite difficult

3.6. Hybrid approaches

An automatic fabric defect detection method has superior sides while at the same time it may have some deficiencies in some respects. So, many researchers carried out defect detection more effectively using a combination of two or more techniques. The main objective here can be said to be minimizing the computational complexity and increasing the rate of defect detection. Han and Xu [86] used template matching method and thresholding method together to find small-sized fabric defects. In this method, template-matching method was developed by obtaining statistical data from the fabric texture. Mak et al. [40] detected fabric defects using previously trained Gabor wavelet networks and morphological elements having linear structural element. In gold image extraction method, certain types of fabric defects were identified successfully by using wavelet transform and statistical methods together [87,88]. However, this technique fails during thresholding stage due to a high ratio of contrast in fabric images with black and white patterns. In another study [89] seven different types of fabric defect were detected through the multi-fractal features and support vector data description model. This study used this method by improving it through adding four new features to its fractal characteristics. Venkatesan et al. [90] extracted contrast, correlation, homogeneity and energy features of the obtained images through the gray level co-occurrence matrix technique by calculating wavelet transforms of defected fabrics. These extracted features were classified by Adaptive Neuro Fuzzy Inference System (ANFIS). In another current study [91], defect detection was made on regular structured fabric images using Gabor filters and Principal Component Analysis (PCA) methods together. The size of the property was reduced through

Table 3
Strengths & weaknesses of fabric defect detection of model-based and learning approach methods for well-known fabric and defect types.

Methods	Strengths	Weaknesses
Autoregressive method	• Examined the linear relationship between pixels • Fast computation • Circular autoregressive model is invariant to rotation • Suitable for fabric images with stochastic pattern variations	• Sensitive to lighting and noise • Low detection rate well for fabric images with large-size and irregular
Gauss Markov Random Field Method	• Can be used with statistical and spectral methods • Thanks to isotropy feature, suitable for segmentation applications • Capture the local texture orientation information • Useful for modeling fabric textures	• Cannot detect small defect • Insufficient in terms of global texture analysis • It is not invariant to rotation and scaling
Learning approach	• Ability to learn complex non-linear input-output relationships • Effective working due to different training methods • Real time performance is highly suitable for industrial application • Utilizable in weaving and knitting machines to detect and identify defects	• Intensive computation for large-size feature vector

PCA method by removing the attributes of the fabric images obtained from TILDA database with Gabor filters. The differences between the results were also highlighted by comparing Euclidian norm and the L_1 norm. Halimi et al. [92] used morphology technique and geometric shape data to detect small defects on the fabric surface. They were able to identify the defect by applying Sobel edge detection and morphology processes to the images. They determined the type of defect by measuring the domain, environment and the density of images obtained. Eldessouki et al. [93] proposed a fabric pilling evaluation system using the morphological operators and statistical Spearman's coefficient. To obtain the extent of pills on the fabric image, they calculated both the area ratio and density features. They used the ANN classifier and obtained robust results. Sparse coding (SC) and small-scale over-completed dictionary (SSOCD) were also applied to fabric defect detection and obtained high detection rate [94]. This hybrid method was implemented on a parallel hardware platform (TMS320C6678). The proposed method can meet the requirements of real time inspection. When the studies are analyzed, it can be said that using together such statistical methods as wavelet transform, which is quick, and gray-level co-occurrence matrix, which is effective, will give effective results.

3.7. Comparison studies

Since a large number of fabric defect detection methods are found in literature, comparisons between these methods have great significance. Therefore, the comparisons of different studies were carried out in the literature. These studies guide researchers and offer the most suitable methods according to the type of fabric and defect among methods. However, it must be considered that studies conducted use different databases, different imaging systems and different parameters. For this reason, while interpreting studies, key parameters such as resolutions of the images used in the study, the calculation complexity, performance indicators and the number of citations should be carefully evaluated. For example, high-resolution images provide precise easiness in defect detection; while in real-time systems, they lead to high computational cost. Baykut et al. [95] conducted a study comparing the methods of Markov random fields, two-dimensional report filters, FFT, KL transform, Laws filters and co-occurrence matrix. Each of these methods has different parameters. Markov Random Fields method was suggested to be the best result. Lee [96] conducted a study comparing the wavelet transform and matching masks methods on eight different types of fabric defects. As a result of experimental applications he made, the best result was found to be matching masks method that used two-dimensional filters. Conci and Proença [97] compared Sobel edge detection, fractal dimension and thresholding methods in order to determine twelve different types of fabric defects, and expressed that the most reliable result was obtained from fractal dimension method. In a recent study [98] regular tape, Gabor filters, wavelet transform, computer vision and digital image processing methods were compared. Of those methods, whose accuracy rates are ranging from 99.40% to 65%, regular-band approach is the method that works best. However, in the fabric images that contain many defects, Gabor filters approach is expressed to be the method with the highest accuracy rate with an accuracy rate of 96% [99].

4. Summary

Textile quality is traditionally human-oriented analyzed. However, this manual method leads to lower productivity and higher market losses. In this study, automatic and online-offline working fabric inspection methods were examined in seven sub-groups. An excellent method that can run on all types of fabric and contain these types of defects has not been found. Also, there are very few automatic and real-time systems that are capable of functioning on weaving and knitting machines. Specifically, an automatic and real-time defect detection system, which has the characteristics of generality and validity on knitting machines, gives information about the defect to the operator, and stops the machine, has not been developed.

Table 1 summarizes the strengths and weaknesses of statistical methods. Although spectral approaches give quick and effective results of fabric images analysis in the frequency domain, they can usually work in regular texture patterns. Table 2 summarizes the strengths and weaknesses of the spectral approaches. Table 3 summarizes model-based approaches that examine the local and global relationships of the pixels and whose computational cost is low, and the strengths and weaknesses of the learning approaches which are widely used in image processing and fabric defect detection.

5. Conclusions

This paper presents a survey of fabric defect detection approaches examined in about 99 references. These approaches have been classified into seven categories: Structural, statistical, spectral, model-based, learning, hybrid and comparison. The main ideas of these approaches along with their strengths/weaknesses have been discussed.

When the developed methods are examined, each of the vast majority of all the studies is seen to create its own database. Once the image database was being built, images were either obtained from factory environment, or brought to the laboratory and database was created with the proper lighting setting. Therefore, the reliability and validity of the methods is far from objectivity. Some studies have used TILDA [80] fabric database. However, this database is difficult to be obtained by all participants as it is to be paid. Also, Hanbay et al. [28] constructed a novel fabric database by using a conveyor system which has line scan camera and linear light. This database contains 3242 defected and 5923 defect-free fabric images. For the development of objective and reliable methods, anonymously accessed free fabric databases are needed.

In the literature search, studies on yarn and fibers, which are the basic building blocks of woven and knitted fabrics, are found to be vanishingly small in number. On the other hand, fabric defects that may occur could be avoided thanks to the evaluation of yarn and fibers before the production of fabric. In some previous studies, smart yarn modeling and rating systems have been developed by examining yarn surfaces [44]. In a review study, some studies conducted on yarns and fibers were examined and a current study is not found. It is thought that serious studies similar as this one are needed for fabric defect detection, and therefore the studies will contribute to the textile industry.

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