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Fabric Defect Analysis In Textile Manufacturing: Evaluating Methods For Generic And Jacquard Fabrics

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Abstract: Regarding maintaining product quality and satisfying customer expectations, fabric defect analysis is vital in textile manufacturing. This research provides a comprehensive assessment of many techniques used for analyzing and pinpointing flaws in standard and Jacquard textiles. This study considers machine vision systems and AI-based algorithms as two examples of cutting-edge automation alongside more conventional human inspection procedures. Manual inspection techniques are extensively reviewed in the first section, with particular emphasis on these techniques' inherent subjectivity and resource inefficiency. More objective and effective defect detection techniques are highlighted as a solution to the problems caused by human bias. The research then looks into automated methods, examining how recent developments in image processing, computer vision, and pattern recognition have the potential to greatly improve the accuracy and speed with which defects may be detected. The major emphasis of this investigation is the use of AI, namely machine learning and deep learning models, for fabric defect identification. This demonstrates how AI may revolutionize textile manufacturing by automating flaw identification and categorization processes. Accuracy, efficiency, scalability, cost-effectiveness, and adaptation to varied fabric compositions, such as basic and complicated Jacquard textiles, are only some aspects considered throughout the evaluation. In addition, the research addresses the problems and opportunities in the field of fabric defect analysis right now. The paper presents prospective improvements, such as hybrid methods and real-time monitoring systems, to solve current constraints and pave the way for a more robust defect analysis framework. These innovations aim to contribute to sustainable practices and customer happiness in the textile manufacturing industry by fostering effective quality monitoring and production optimization. In conclusion, this study provides a thorough comprehension of fabric defect analysis procedures, which is helpful for professionals and academics in the field. The results fuel the never-ending development of quality assurance techniques, resulting in improvements that raise standards, shorten production times, and give the textile business a fighting chance in the market.
Keywords: Fabric defect analysis, textile manufacturing, defect detection, Jacquard fabrics, generic fabrics.

1. Introduction

Weaving and knitting machines are the workhorses of the textile industry. Textile fibres are the raw material for making fabric. Cotton is a common example of a natural ingredient used in producing textile fibres. A fault in the produced fabric surface is a fabric defect. In particular, issues with the machinery, flawed yarns, machine spoils, and excessive stretching all contribute to flaws in the fabric. The textile industry has classified more than 70 fabric flaws [1]. Defects often lie along or perpendicular to the direction of motion. Textiles ' two most common surface flaws are surface colour change and local texture irregularity [2]. Figure 1 depicts six typical flaws in textiles. “Slubs (Fig. 1(c)) may be formed by thick spots in the yarn or by fly waste being spun in yarn during the spinning process, whereas the breakage of needles generates float (Fig. 1(a)).”

An example of a mechanical problem induced by a damaged machine component is shown as a hole in Fig. 1(d). A typical textile flaw is stitching, as seen in Fig. 1(e). This flaw occurs if the primary or secondary loom mechanisms are inadvertently moved. Lubricants and rust generate rust spots (Fig. 1(f)). Serious flaws prevent the cloth from being sold, meaning money is lost [3]. A device that can identify flaws in the fabric helps make safer, higher-quality goods. Therefore, there is a growing need for automated fabric flaw-detecting systems to ensure the highest quality textile production. This automated device can detect flaws in the fabric's surface using image and video processing methods.

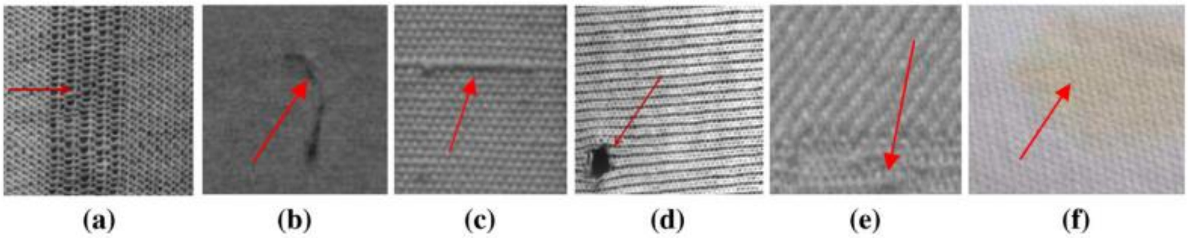

Fig 1: Needle breaks, curled weft, slubs, holes, sloppy stitching, rust stains, and broken needles are some common textile flaws. (The arrows show the broken lines.).

Fabric defect detection is the procedure through which the position, kind, and magnitude of fabric flaws are identified. Fabric flaw identification often relies on human examination. Errors caused by negligence, optical illusion, and tiny faults are instantly corrected, although human examination cannot discover them [3-5]. Workers are prone to boredom, leading to incorrect, uncertain inspection findings during human inspection, which fails to detect faults in terms of accuracy, consistency, and efficiency. As a result, automated fabric inspection is a promising approach to enhancing fabric quality [6, 7]. Automated inspection is a method of finding flaws in a product as it is being manufactured. These systems are capable of stopping production at the precise moment a flaw is found, allowing for real-time inspection. When a problem is detected, automated systems may provide the operator specifics [8-10]. In the following paragraphs, I will describe the many parts of an automated defect detection system. Ngan et al. [7] recently surveyed 139 works on detecting textile flaws. They did a more thorough categorization, dividing methods into seven categories. They were also separated into two groups: motifs and non-motifs. However, most of the publications evaluated deal with issues with woven fabrics. As a result, the article needed to thoroughly analyze the issues that might arise with circular knitting fabrics.

However, there needed to be more detail on the picture capture system's constituent parts. Mahajan et al. [2] earlier published a review study on the topic of fabric inspection. Now, three defect detection techniques are used: statistical, spectral, and model-based. The fundamental issue with this work was that it only considered uniform fabric textures, but many types of cloth have irregular patterns. The second issue with [2] is that, like the prior technique reviewed in [7], details regarding the picture capture equipment need to be provided. This study provides the current best practices for detecting fabric defects using various methodologies, including structural, statistical, spectral, model-based, learning, hybrid, and comparison approaches. “Our paper's primary contributions are as follows: It provides a more thorough breakdown of methods into seven distinct groups (structural, statistical, spectral, model-based, learning, hybrid, and comparative).” It also includes a qualitative evaluation of each approach. Each technique's advantages and disadvantages and whether or not it may be used to create materials suitable for weaving and knitting are outlined. It offers a comparison of options for the image capture system's components.

2. Fabric Defect Detection Methods

In this study, we divide the methods for detecting flaws in fabrics into two groups: the first, known as classical algorithms, and the second, known as learning-based algorithms (Figure 1). Most traditional algorithms are founded on "feature engineering with prior knowledge," which includes statistical, structural, spectral, and model-based methods. “The learning-based algorithms may be further broken down into two categories: classical machine learning algorithms and deep learning algorithms.” Machine learning has been more popular recently and has shown outstanding outcomes across various industries. Mathematical algorithms learn from and analyze data to generate predictions and judgements in machine learning.

2.1 Traditional Algorithms

A. Statistical Algorithms.

The geographical distribution of grey values in images is used in various statistical approaches, such as grey-level co-occurrence matrices (G.L.C.M.), autocorrelation analysis, and fractal dimension features [8].

The GLCM-based automatic fabric flaw identification system presented by Raheja et al. A SIGNAL GRAPH IS BUILT using G.L.M.C. statistics and the distance between pixels. The test picture is then compared to the non-defective image. In addition, a Gabor filter-based technique is used for fault detection. Higher detection accuracies and reduced computing complexity are drawn from using GLCM-based algorithms [9, 10]. By deriving the eigenvector of the defect, Anandan et al. [11] combine the G.L.C.M. and curvelet transform (C.T.), highlighting the fabric defect characteristics. Experiments demonstrate the efficacy of the suggested algorithm when compared to G.L.C.M. and wavelet-based approaches.

An eigenvalue-based statistical method for flaw detection in fabric pictures was developed by Kumar et al. [12]. Images of damaged areas of cloth are analyzed using the coefficient of variation. This procedure is straightforward to implement based on the studies shown.

The membership degree of each fabric area is calculated by Song et al. [13] to identify fabric problems effectively. The image's extreme point density map is used with the membership function region's characteristics to determine the prominence of defect areas. In addition, a threshold strategy and morphological processing are used across the whole scheme. The author claims his system can reliably and quickly identify flaws in fabric despite interference from noise and background textures.

Gharsallah et al. [14] describe a fabric flaw-detecting method using an enhanced anisotropic diffusion filter and saliency image characteristics. The latter combines the local gradient magnitude with a saliency map to distinguish the faulty edge from the background texture, which is beyond the capabilities of standard anisotropic diffusion algorithms. This method can eliminate the textured backdrop while keeping the faulty edge in the picture.

Several statistical techniques for detecting flaws in textile fabrics are summarized in Table 1.

Table 1: Algorithms for statistically detecting flaws in textiles

Author	Proposed method	Dataset	Evaluation
Sayed [15]	Minimum-error thresholding and entropy filtering	T.I.L.D.A. dataset	Detection success rate
Kumari [16]	Similarity calculation based on Sylvester matrices	KTH-TIPS-I and KTH-TIPS-II	False positives and false negatives
Chetverikov and Hanbury [17]	Based on two fundamental structural properties, regularity and local orientation (anisotropy)	Brodatz images and T.I.L.D.A. dataset	Detection success rate

B. Spectral Approach.

Many other spectrum approaches exist, but some of the most well-known are the Fourier transform, Gabor transform, wavelet transform, and discrete cosine transform [18–20]. Table 2 details the algorithms discussed in this survey. “Fabric defect detection applications have been extensively researched and validated using Fourier transform, wavelet transform, and Gabor transform-based approaches.”

Li et al. [21] proposed automated fabric flaw identification using a multiscale wavelet transform and a Gaussian mixture model. The "Pyramid" wavelet transform was used to break down a fabric picture, and the thresholding technique was then used to rebuild the original. The rebuilt picture was then segmented using the Gaussian mixture model. “The results of the trials show that the suggested method is capable of accurately identifying and segmenting pictures with defects.”

Using local homogeneity information and the discrete cosine transform (D.C.T.), Rebhi et al. [22] describe a fabric flaw identification method. After recalculating the homogeneity picture, D.C.T. was applied, and various energy characteristics were retrieved from each D.C.T. block. Then, the feedforward neural network classifier is used to make sense of the data.

Table 2: Fabric flaws may be detected using spectral techniques.

Author	Proposed method	Dataset	Evaluation
Sulochan [23]	Fuzzy C-means clustering with multiscale wavelet features	Real and computer-simulated	fabric image Detection error rate
Vermaak et al. [24]	Complex wavelet transform with two trees	(D.T.C.W.T.) T.I.L.D.A. dataset	Detection success rate
Liu and Zheng [25]	information entropy and frequency domain saliency are the foundations of this technique.	Industrial Automation Research Laboratory Research Associate's Data Set	A.C.C., true positive rate(T.P.R.), false positive rate(F.P.R.), positive predictive value (PPV), negative predictive value (N.P.V.), time, F-measure
Di et al. [26]	In order to get the quaternion picture's saliency map, we use the L0 gradient minimization method and the 2D-FRFT.	Hong Kong University's Automation Laboratory Fabric Database Dataset	True positive (T.P.), false positive (F.P.), true negative (T.N.), and false negative (F.N.)
Jing [27]	Image removal using Gabor filters and a golden frame	University of Hong Kong's Industrial Automation Lab and the T.I.L.D. database	Detection success rate
Mohammed and Alhamdani [28]	Gabor feature-enhanced fuzzy back propagation neural network	Collected dataset	Detection success rate
Yapi et al. [29]	In the contourlet space, using local textural distributions learned by reinforcement learning	T.I.L.D.A. database	(T.P., F.P., TN, and F.N.) local precision (P.L.), local recall (R.L.), and local accuracy (A.C.C.L.)

2.2 Learning-Based Algorithms

A. Classical Machine Learning Algorithms

(1) Algorithms That Use A Dictionary To Learn New Words. Dictionary learning-based algorithms are effective in several studies in detecting flaws in textile fabrics. "In general, these algorithms begin by learning a vocabulary from the training or test picture, then rebuild a fabric image free of defects using the dictionary, and then execute detection by subtracting the rebuilt image from the test image." In fabric defect inspection, low-rank representation-based algorithms have recently emerged. Many techniques convert the low-rank decomposition issue to the nuclear minimization (N.N.M.) problem to optimize the objective function.

An algorithm is proposed by Li et al. that is inspired by models of biological vision. Using a low-rank representation (L.R.R.) model of biological visual saliency, we can separate the fabric picture into more noticeable defect parts and background regions that are less noticeable [30].

By contrast, Li et al.'s [31] work modelled the defect area as a sparse structure. Because of this, we may think of a fabric picture as the combination of a low-rank matrix and a sparse matrix. The described technique employs eigenvalue decomposition on the blocked image matrix to reduce dimensionality instead of singular value decomposition (S.V.D.) on the original image matrix. Therefore, this technique is simple and effective, provided the cloth picture has enough contrast.

Two problems with the low-rank decomposition are highlighted by Shi et al. [32]. One issue is that current low-rank decomposition models must better pick out faulty zones with strong gradients. Another drawback is that accurate background knowledge leads to proper segmentation of complicated or tiny fault areas. Shi et al. propose a low-rank decomposition method that combines gradient information with a structured network technique to overcome these constraints. The proposed method achieves better results than existing methods on the point, box, and star databases.

Common examples of traditional machine learning approaches used for fabric fault diagnosis are K-Nearest Neighbor (K.N.N.) [33] and neural networks [34]. Feature engineering is a crucial part of building any machine learning system. Mak et al. [35] used support vector data description (S.V.D.D.), a support vector machine learning technique for one-class classification, to locate textile flaws.

To solve this problem, Zhang et al. suggest using a network of radial basis functions (RBFs). Using a Gaussian mixture model (G.M.M.) improves the precision with which Gaussian RBF parameters are estimated. The proposed method is effective on several classification datasets. [36]

Fabric flaws may be identified using an autoencoder-based technique, as proposed by Tian and Li [37]. Using the recurring texture pattern, we identified nearby nondefective patches comparable to each possible defect patch. We then weighted and aggregated the related latent variables to alter the original latent variable. The experimental findings show the efficacy of the suggested algorithm.

This issue is treated as a binary problem by Yapi et al. [38]. "To distinguish between the defect and nondefect classes, a Bayesian classifier (B.C.) was utilized to extract a compact and accurate feature set by statistical modelling of multiscale contourlet decomposition. This method achieved very accurate detection in real-time."

B. Deep Learning Algorithms.

The quality of textile products and the efficiency with which they are produced [41] have benefited greatly from the recent application of deep learning approaches to the issue of fabric defect identification [39, 40]. However, there are still challenges in using deep learning algorithms within certain sectors despite their efficacy when dealing with segmentation and classification difficulties [42]. In the first place, the algorithm has to execute quickly and reliably in real-time since this is a need of the textile manufacturing line itself. Furthermore, faulty picture data is more difficult to collect than typical defect-free samples, which presents difficulties in the training process of deep learning [43].

One-stage and two-stage detectors are now available for the deep learning-based object detector [44]. "Table 5 lists some of the traditional deep-learning techniques used for object identification." In most cases, the detection accuracy of one-stage detectors falls short of the necessary standards, but their high detection speed makes them suitable for online detection. While the detection accuracy of two-stage algorithms is better, this speed makes it challenging to match the algorithm's real-time needs in production situations. Like other areas, the pros and cons of one-stage and two-stage detection methods hold in fabric defect identification. The two-stage technique is more precise than the one-stage but is more time-consuming to implement. If the detection accuracy can be met, the quicker the detection speed will be in its practical use in the textile sector. The algorithm must be chosen in light of specific use cases to strike a good balance between speed and precision.

- Single-Pass Detection Methods. There is no proposal creation step in a one-stage detection technique. These algorithms typically consider every pixel in the picture a candidate for an object and successfully label each interest zone as either a target item or a background.

One one-stage detector proven effective in object identification is the newly suggested single-shot multi-box detector (S.S.D.). This algorithm takes its cues from the structure of a CNN. Liu et al. [45] have made certain enhancements to the textile defect scenario, and the experimental results demonstrate the rationale and efficacy of these changes.

A CNN-based algorithm for on-loom fabric flaw inspection is presented by Ouyang et al. [46]. The proposed technique augments a convolutional neural network (CNN) with a dynamic activation layer that uses defect probability data and a paired potential function. This technique performs well on the challenge of classifying data that is not evenly distributed.

Algorithms based on deep convolutional neural networks (D.C.N.N.s) have seen widespread industry use due to their successful performance on visual tasks. D.C.N.N. is used by Liu et al. [47] to identify flaws in fabrics with intricate patterns. This method is tailored for a practical, low-budget textile manufacturing setting. The detection has been made more reliable by several tweaks. Zhou et al. propose Efficient Defect Detectors (E.D.D.s), a D.C.N.N. architecture tailored specifically to the issue of fabric defect detection [48]. E.D.D.s use a scaling approach to modify the input's resolution, depth, and breadth to extract additional low-level data. When compared to standard fabric fault-detecting methods, the enhancement was superior.

3. Conclusion

An extensive literature evaluation on smart manufacturing techniques for automatically detecting fabric defects is presented in this research. “Traditional and learning-based algorithms are the two broad groups into which all the approaches discussed here fall.” No hard lines can be drawn between the various classifications. Scientists typically use multiple algorithms to get a more accurate detection. In addition to suggesting avenues for further study, the survey's findings confirm that synergistic approaches provide superior outcomes. “For completely automated web detection systems, precise, efficient, and reliable fabric defect detection algorithms are required.”

The use of computer vision for autonomous textile fabric flaw identification has garnered much interest from scientists. Advances in object identification algorithms, processing power, and sensor technology and industry promise rapid progress in computer-vision-based textile flaw detection methods.

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