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AN AIRBAG FABRIC INSPECTION FRAMEWORK

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The production process of airbags demands near-zero defects, from raw materials to final assembly. To minimize fabric flaws, we conducted a study on the maintenance schedule of looms using a custom-designed vision system at a leading global manufacturer. We identified and classified all observable defects in the resulting fabric based on the proposed framework, which utilizes wavelet transform and supports high-speed processing. The results were correlated with loom maintenance and monitored over a two-year period to reduce unforeseen errors. As a result, the company successfully rescheduled repairs, decreased defects, and minimized material loss.

1. INTRODUCTION

In the modern sense, quality is a complex, relative, and dynamic concept that encompasses technical, economic, aesthetic, and ergonomic requirements, whose content evolves in response to social needs and is measured by the value and economic efficiency provided by the product or activity. Quality is of primary importance in every aspect of a business. A good quality product is a product that meets the purpose for which it was created and satisfies a specific customer need. Therefore, quality control involves a systematic and regular examination of variables that impact the quality of a product. Conforming to the integrated management system, the zero defects strategy is based on the principles of "at the right place, with the right parts and the right process", as well as continuous process improvement. Especially in the automotive industry, quality control services verify the quality of raw materials entering the manufacturing process, as well as the technological process operations, and the quality of both unfinished and finished products, by ISO/TS 16949 standards.

In public transportation safety, besides the use of safety belts, the development of airbags has introduced another passenger protection system in the event of a car crash. The first airbags were made available around the 70s and were marketed under the following designations: supplemental restraint system (SRS) or supplemental inflatable restraint (SIR). Even if the first systems were quite unstable, the primary interest of car manufacturers has led to the development of an industry that has proven beyond a doubt to save passengers' lives. The first car to utilize such equipment was the standard Porsche 944, introduced in 1987.

The airbag can be seen as passive security equipment (because the human does not intervene in triggering), comprising a set of sensors, an electronic control unit, and a pyrotechnic cap that fills a fabric bag coated on one side with a silicone film with hot air. Triggering is performed considering several factors, including deceleration, impact, and speed. The electronic will deploy the safety car systems, the airbags, and/or the pre-tensioned seatbelts. To inflate the airbag, a pyrotechnic device called an initiator releases a gas at approximately 100 °C after several stages (20 to 40 ms) within the fabric bag. The quick inflation process ensures that the car passenger touches the surface of the cushion during the recession/deflation moment, produced by a small ventilation hole, and hits a soft surface as the effective speed of opening is approximately 300 km/h. These ventilation holes play a crucial functional role, as they regulate the amount of gas inside the cushion during a crash. It's slow deflation produces the amortization of the passenger and the dissipation of collision energy. Airbags are designed to trigger at impacts with a force comparable to a wall crash at a speed of 13-23 km/h. This impact force is the equivalent of a front collision at the speed of 45 km/h to a parked car, as the deforming structure absorbs the shock.

Few authors have explored the application of texture segmentation and recognition to the airbag weft, as in [1] or in a comprehensive textbook [2]. In this paper, textile defect detection is investigated using a bank of Gabor filters. Section 2 presents the process of airbag production, together with the tools used for weaving. In Section 3, a state-of-the-art review of texture detection and recognition, with applications in the textile domain, is described. In section 4, the proposed framework for texture inspection and defect detection is introduced. Section 5 reports our experimental results, followed by conclusions.

2. AIRBAG FABRIC PRODUCTION

Weaving is one of the most critical stages in the manufacturing process of airbags. Therefore, the quality of fabrics must be higher and provide a low air permeability to prevent structural tears or hot gas leaks in the inflation process. The special type of threads employed here creates a low-weight, low-thickness, and high-strength fabric with the specifications outlined in Table 1.

The weaving looms used are water jet TOYOTA LW 601 type, with the following operational parameters:

- Weaving width: 2.3 m;
- Weaving speed: 40 m/ h;
- Weave type: 1:1 plain 4 threads;
- Water jet pressure: P = 2 bar;
- Water temperature: T = 17±2°C.

Looms are supplied with warp from a previous process operation, while the weft thread comes from a spool. The primary material is the fabric that serves as the airbag's structural component; in this case, the core material is a plain fabric made of 6.6 polyamide with a thin layer of silicon overlaid. Specifications include a 46x46 threads/inch density fabric, made with 470 dtex yarn count and comprising a total of 68 filaments, featuring an S twist. These threads are composed of 100% continuous Nylon 6 yarn of high tenacity, exhibiting excellent elastic recovery. At low stresses, they recover almost 100 %.

Polyamide 6.6 is part of the group of synthetic fibers produced by melt spinning. Polyamide 6.6 materials are formed from adipic acid and hexamethylene diamine, and after a polycondensation reaction, the processes involve spinning and cooling to form Polyamide 6.6.

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Table 1

Airbag fabric properties.

Fabric Characteristics	Specification
Weight	210-240 g/m^2
Thickness	0,27-0,35 mm
Density	46 yarns/inch
Air permeability	≤ 10 l/dm²/min
Tenacity	≥ 500 N/cm
Elongation	≥20 %
Tear resistance	≥175 N

Other properties of airbag polyamides include a moisture regain value of 5%, a relatively low melting temperature of 215°C, and a softening temperature of 175 °C. Additionally, it exhibits excellent abrasion resistance and good tensile strength, but is sensitive to chemicals, light, and microorganisms. The atmospheric conditions (temperature and humidity) in which fibers are deposited have a significant influence on these fabric characteristics.

Fig. 1 – The Toyota water jet loom used for airbag fabric.

The silicone layer coating of the fabric will offer properties such as dimensional stability, low air permeability, and increased resistance to heat during airbag inflation at approximately 300 °C. This operation is quite complex, involving many parameters that could somehow deteriorate the fabric. The workflow comprises the drying of the raw material, vacuuming of the fabric, the coating with several components: an elastomer, a silicone rubber, a pigment, and the final drying in a series of ovens. Then, the material follows the technological flow and gets to the cutting stage, after which all parts of the product are assembled using sewing threads.

3. IMAGE PROCESSING FOR TEXTILE DEFECT DETECTION

The textile industry has the lowest rate of automation; therefore, in recent years, considerable research and development efforts have been made in this direction. Image processing was one of the first techniques that was applied to various stages of the production process. Existing resources [3] have developed a high-speed algorithm for defect detection in textiles based on estimating the fractal dimension and a simple box-counting method. Chan and Pang [4] have presented a method based on the analysis of discrete Fourier transforms, classifying defects into four types: double yarn, missing yarn, webs or broken fabric, and yarn density variation. Other authors [5,6,21] have detected defects in randomly textured surfaces that arise in sandpaper, castings, leather, and many industrial materials using an image reconstruction scheme from the Fourier transform.

Nevertheless, Gabor filters are a fast and reliable method of highlighting flaws in textured materials. After applying the filter, several post-processing and segmentation phases are required to isolate and identify the actual defects. Examples of such processes are given in [7,8].

An essential property of the wavelet transform is the shift invariance, which means it can be used to investigate fabric images at different scales. Analyzing defects based on 1-D wavelet transformations applied on the horizontal and vertical projection signals can lead to a final classification approach with various techniques [9]. The authors in [10] further developed the idea of using the Karhunen-Loeve transform to process texture images and a Markov random field as a discriminative classifier.

More up-to-date papers are balancing the use of pattern extraction and recognition methods [11], combined feature classification by random forest [10], or deep learning with the “all-purpose” convolutional neural networks [12,13]. In the paper by [14], the authors introduce AC-YOLOv5, a novel method for textile defect detection designed to overcome the challenges posed by complex textures, varied defect sizes, and target diversity. By integrating the ASPP module for multiscale feature extraction and the CSE attention module for enhanced defect detection, it significantly improves accuracy and stability. Tested on a real-world dataset, AC-YOLOv5 achieved an impressive 99.1 % detection accuracy, meeting the needs of industrial applications.

Using deep learning with long short-term memory, textile defect detection and texture classification become highly efficient, replacing traditional manual inspections. In paper [15], the process implemented analyzes digital images to identify fabric defects, even in complex patterns, with faster computation. The approach involves RGB image conversion, threshold comparison, and unsupervised learning for defect percentage classification, utilizing multi-scale curvelet decomposition to enhance pattern recognition and defect detection while reducing computational time.

Buoy capsules, made from composite materials, present challenges for defect detection due to material anisotropy. The paper in [16] introduces a data-driven method for defect detection using stress wave measurements. By analyzing strain signals with VMD and utilizing a GenSVM model for defect recognition, the approach demonstrates effective detection and health management of the capsule.

The review paper [17] discusses the application of computer vision and digital image processing in fabric defect detection, a crucial task in the textile industry. The article reviews various computer vision-based methods, including histogram, color, image segmentation, dictionary learning, texture analysis, frequency domain operations, gray-level co-occurrence matrix, feature fusion, sparse methods, morphology, and deep learning, highlighting their effectiveness in addressing these limitations. Additionally, it evaluates performance criteria for automatic defect detection, explores limitations of current research, and suggests future directions for improvement.

The study in paper [18] proposes a fabric defect detection model using a cascade R-CNN to address challenges in automatic fabric defect detection and eliminate the deficiencies of detection algorithms based on convolutional neural networks. The model incorporates block recognition, detection box merging, and switchable atrous convolution layers to enhance feature extraction. Experimental results demonstrate the model's effectiveness in accurately detecting fabric defects, tiny ones, in high-resolution images.

The authors of [19] introduce a texture defect detection (TDD) algorithm that utilizes pre-processing to extract the luminance plane, wavelet decomposition to split the image into multiple sub-bands of the exact resolution as the original, and statistical features with support vector machines. The TDD method achieves 96.56% accuracy in detecting fabric defects, with real-time validation showing 97% accuracy.

The improved, faster R-CNN deep learning algorithm proposed in the paper [20] integrates an E-FPN (enhanced feature pyramid network) for better multi-scale feature extraction, replaces the ROI (Region of Interest) Pool with ROI Align to improve segmentation and small target detection, and uses a Light Head to accelerate network performance. An average precision of 97.2 % and a detection time of 23.73 ms are the metrics achieved by the enhanced algorithm, which significantly outperforms the original method in both accuracy and practicality.

4. A NOVEL SYSTEM FOR ON-LOOM DEFECT DETECTION

We propose a novel algorithm, as illustrated in Fig. 2, which outlines the processing stages and data block flow. Some supplementary details and required optimizations for real-time processing, along with the blocks, will be described individually further.

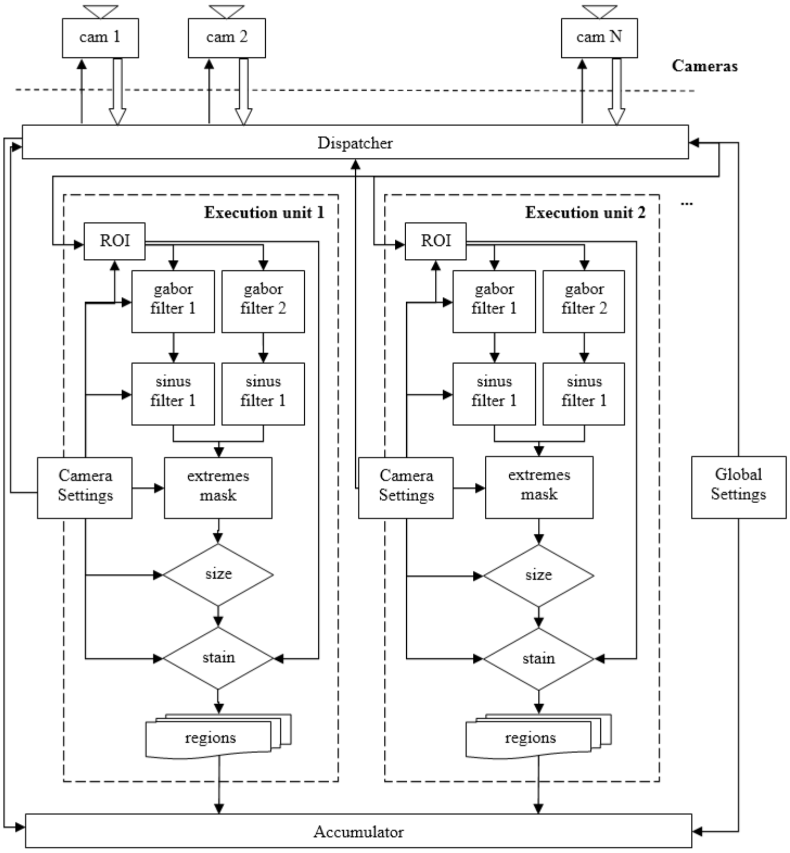
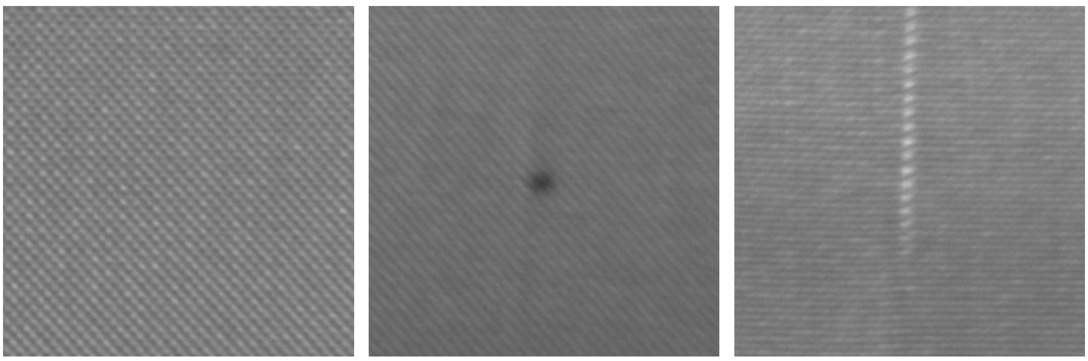
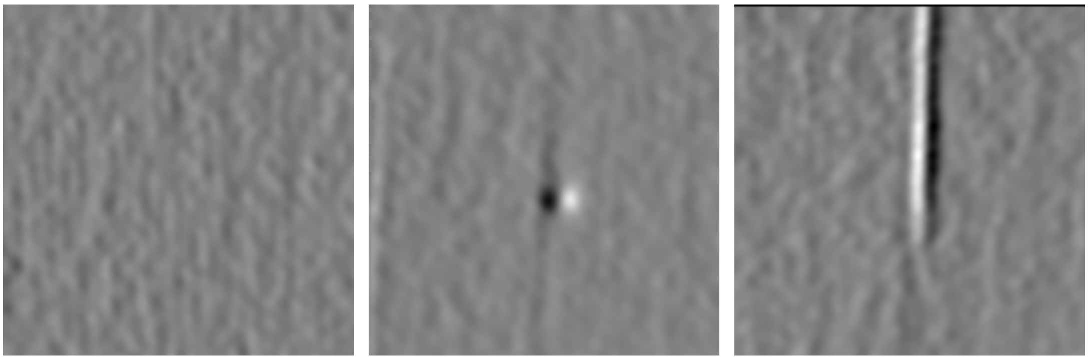


Fig. 2 – Data flow block schema.



a) b) c)

Fig. 3 – Image acquisition a) without defects; b) stain defect; c) thick yarn defect.



a) b) c)

Fig. 4 – Resulting images after Gabor filtering; a) without any defects; b) with stain defect; c) thick yarn defect.

The test images presented are cropped from 5M pixel acquisitions. The Dispatcher Block manages the acquisition of the images; the trigger is a timer or the condition when the accumulator finished collecting the last iteration's results. The cameras are configured before each acquisition with the camera specific exposure time. After collecting the images from all the cameras, it starts the execution units in parallel. The region of interest block cuts out the parts of the image which are either borders, region of fabric or undesired background which isn't part of the fabric (like a component of the loom). The ROI manually configured for each camera individually.

The Gabor filter block applies a Gabor filtering to the ROI. It first generates a filter with the settings specified in the camera configuration, which are the following: filter size, wavelength, orientation, phase and bandwidth. Afterwards, a convolution with the original image is applied and histogram equalization transposes the results back into 8 bit grayscale values.

The formulas for the filter are presented in equation (1), where λ denotes the wavelength, θ mean orientation (radians), φ denotes the initial phase, γ denotes the aspect ratio (how elliptic is the shape), b denotes the bandwidth and σ represents the standard deviation of the Gaussian factor.

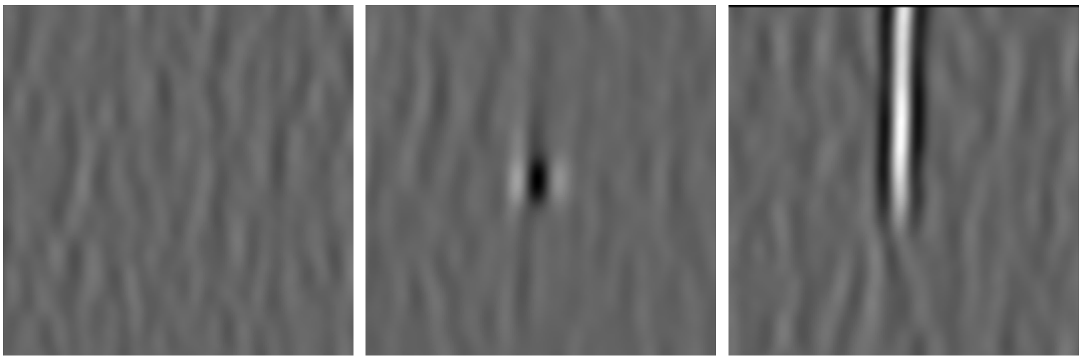
$$b = \log_2 \left(\frac{\frac{\sigma}{\lambda}\pi + \sqrt{\frac{\ln 2}{2}}}{\frac{\sigma}{\lambda}\pi - \sqrt{\frac{\ln 2}{2}}} \right) \quad \frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{\ln 2}{2}}\frac{2^b + 1}{2^b - 1}. \tag{1}$$

One important criterion in deciding the filter size was the execution time, which was limited. The values that fit the texture best were chosen empirically as follows: block size 18px, wavelength 15, orientation 0 or pi/2, phase pi/2, bandwidth 2, aspect ratio 1.7. Smaller sizes for the blocks generate more noise and false detections.

The sinus filter block handles the offsetting of the de-phasing response of the Gabor filtering if a defect is encountered. It constructs a sinusoidal filter of the same size as the Gabor filter and applies a convolution with the image, followed by histogram equalization. There are two Gabor and Sinus filter blocks in each execution unit, since the first deals with the horizontal orientation and the second with positioned along the fabric lines.

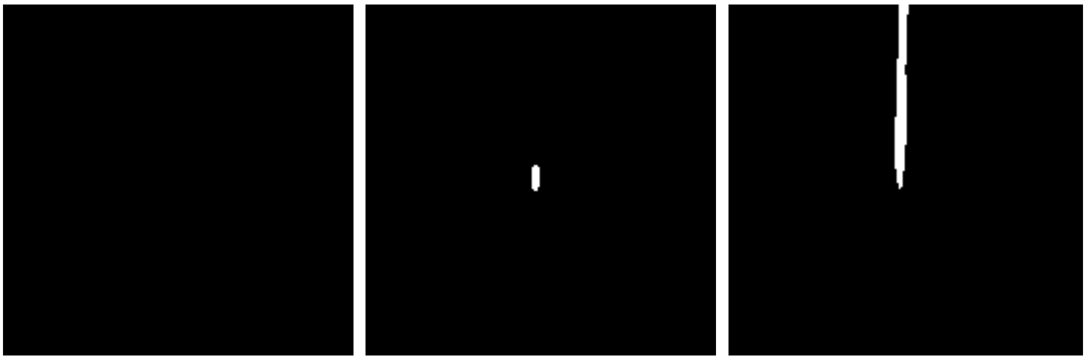
The extreme mask block has the role of extracting regions out of the processed images. The parameters for masking are the lower bound and the upper bound of grey intensity. The image is parsed and all regions obeying the boundaries rules are extracted. The size decision cuts out regions smaller than an input minimum size. The remaining regions cover a larger area of the de-phasing Gabor filter and presume as being part of a defect.

The stain decision averages the grey intensity of the pixels in the defect region, taken from the original image. If this average falls beneath the input threshold, the region is classified as a fabric stain. Otherwise, it is classified as a fabric defect. The accumulator block collects the classified regions from all the cameras, assembles the acquired images from the dispatcher with metadata from the regions and displays the results. If configured, an XML file will be outputted to the disk along with the image, containing the region metadata.



a) b) c)

Fig. 5 – Result images after both Gabor and sinus filter; a) without any defects; b) stain defect; c) thick yarn defect.



a) b) c)

Fig. 6 – Segmented images: a) without defects; b) stain defect; c) thick yarn defect.

5. **RESULTS**

Several tests were conducted to validate the results. In this case, all images were saved and individually tested by a human operator to count the number of false positive cases. We performed supervised validation on two different days, spanning a period of approximately eight and ½ hours. The 6-in-a-row camera acquired a total of 19.687 images. From this total, the system has selected 189 as containing defects, corresponding to 0.96 percent. Two types of defects were detected: oil stains and thick yarns. In the first case, even if the system has responded in the absence of the trained texture, this situation is not considered as a potential defect by the quality control, as it doesn't affect the functionality of the weft, and the appearance is not essential. However, we have also checked the performance of the proposed system and identified 10 false negative situations out of a total of 175 detected stains.

In the case of thick yarns, a total of 30 cases were classified; among them, the human operator reduced the number of actual defects by half, as 14 false positives were saved, resulting in a defect percentage of 0.081.

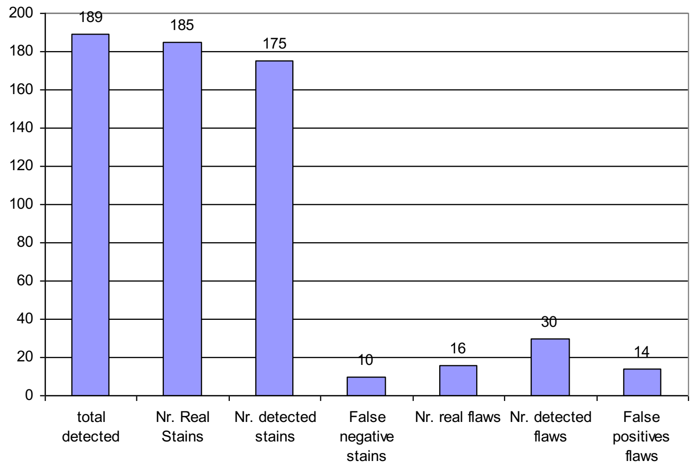
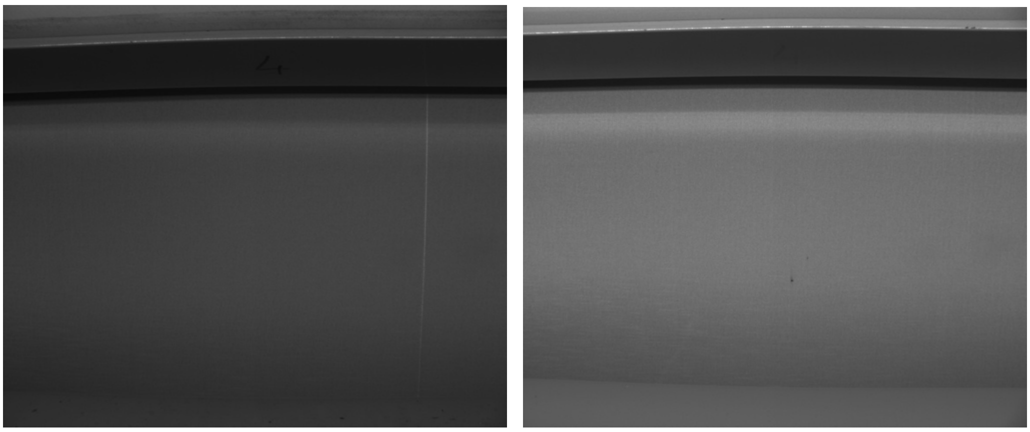


Fig. 7 – Categories of defects detected over 19687 test images.



a) b)

Fig. 8 – Defects acquired images. a) thick yarn, b) stain.

6. **CONCLUSIONS**

The production of airbags is a highly critical and sensitive process that demands an almost zero-defect output, as the reliability of airbags is directly tied to vehicle safety and human lives. The precision required in this process extends from the quality of the raw materials, such as the high-strength fabrics, to the final assembly. Any defects in the material can compromise the airbag's functionality, which is why monitoring and minimizing flaws throughout production is essential.

To address the challenge of fabric defects, we conducted a detailed study focusing on the maintenance schedules of the looms used to weave the airbag material. A key aspect of our approach was the development and deployment of a custom-designed vision system at one of the world's leading global manufacturers. Based on advanced image processing techniques using the Gabor wavelet transform, this system was specifically designed for high-speed operation. It allowed for real-time inspection of the fabric as it was produced, at a speed of 40 m/h and with a resolution of 0.25 mm.

The system can analyze visual patterns by utilizing the wavelet transform, making it highly effective in detecting various fabric defects. These included observable issues such as broken or misaligned threads, irregularities in the weave pattern, and stains, all of which could compromise the integrity of the airbag material.

Over two years, the system continuously monitored and classified these defects, producing a rich dataset that correlated with the looms' maintenance records. This analysis revealed a clear relationship between loom maintenance schedules and the occurrence of fabric flaws. By identifying patterns in the timing and nature of these defects, we were able to recommend optimized maintenance schedules tailored to the actual wear and performance of the looms.

As a result, the manufacturer was able to reschedule loom repairs more proactively, significantly reducing the number of defects and the associated material wastage. This not only enhanced the overall quality of the airbag fabric but also reduced production costs by minimizing downtime and material loss due to defective output. The proposed framework thus provided a practical solution that improved both the efficiency and the safety outcomes of the airbag production process.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

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Andrei Marinică: methodology, software, formal analysis, writing-review.
Raluca Brad: conceptualization, methodology, writing draft, funding acquisition

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REFERENCES

1. J.L. Bouchot, G. Stübl, B. Moser, *A template matching approach based on the discrepancy norm for defect detection on regularly textured surfaces*, Proc. SPIE, **8000** (2011).
2. R. Nayak, R. Padhye, Automation in Garment Manufacturing, The Textile Institute Book Series, Woodhead Publishing (2017).
3. A. Conci, C.B. Proença, *A fractal image analysis system for fabric inspection based on box-counting method*, Computer Networks and ISDN Systems, **30**, pp. 1887–1895 (1998).
4. A. Kumar, G. Pang, *Fabric defect segmentation using multichannel blob detectors*, Opt. Eng., **39**, *12*, pp. 3176–3190 (2000).
5. A. Kumar, *Computer vision-based fabric defect detection: a survey*, IEEE Trans. Industrial Electronics, **55**, *1*, pp. 348-363 (2008).
6. S.P. Dhanalakshmi, R.R.S. Kumari, *A survey of fabric defect detection techniques*, Int. J. Appl. Eng. Res. (2018).
7. K.-L. Mak, P. Peng, *Fabric defect detection using multi-level tuned-matched Gabor filters*, J. Ind. Manag. Optim., **8**, *2* (2012).
8. J.L. Raheja, S. Kumar, A. Chaudhary, *Fabric defect detection based on GLCM and Gabor filter: A comparison*, Optik, **124**, *23*, pp. 6469–6474 (2013).
9. Y. Li, W. Zhao, J. Pan, *Deformable patterned fabric defect detection with Fisher criterion-based deep learning*, IEEE Trans. Autom. Sci. Eng., **14**, *2*, pp. 1256–1264 (2017).
10. N.T. Deotale, T.K. Sarode, *Fabric defect detection adopting combined GLCM, Gabor wavelet features and random decision forest*, 3D Res., **10**, *1*, 5 (2019).
11. G. Vladimir, I. Evgen, N.L. Aung, *Automatic detection and classification of weaving fabric defects based on digital image processing*, 2019 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), pp. 2218–2221 (2019).
12. A. Şeker, *Evaluation of fabric defect detection based on transfer learning with pre-trained AlexNet*, 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), pp. 1–4 (2018).
13. B. Wei, K. Hao, X.-S. Tang, L. Ren, *Fabric defect detection based on Faster RCNN*, Int. Conf. Artif. Intell. Textile Apparel, pp. 45–51 (2018).
14. Y. Guo, X. Kang, J. Li, Y. Yang, *Automatic fabric defect detection method using AC-YOLOv5*, Electronics, **12**, *13*, 2950 (2023).
15. K.S. Kumar, M.R. Bai, *LSTM-based texture classification and defect detection in a fabric*, Measurement: Sensors, **26**, 100603 (2023).
16. M. Wang, Z. Chen, P. Wang, H. Zhu, L. Fan, *Aerostat airbag damage detection based on VMD decomposition and GenSVM*, J. Phys.: Conf. Ser., **2173**, 012056 (2022).
17. A. Rasheed, B. Zafar, A. Rasheed, N. Ali, M. Sajid et al., *Fabric defect detection using computer vision techniques: A comprehensive review*, Math. Probl. Eng., **2020**, 8189403 (2020).
18. L. Li, Q. Li, Z. Liu, L. Xue, *Effective fabric defect detection model for high-resolution images*, Appl. Sci., **13**, *18*, 10500 (2023).
19. T. Meeradevi, S. Sasikala, *Automatic fabric defect detection in textile images using a LabVIEW-based multiclass classification approach*, Multimed. Tools Appl., **83**, pp. 65753–65772 (2024).
20. L. Luo, C. Deng, Z. Wu, S. Wang, T. Ye, *Automobile airbag defect detection algorithm based on improved Faster RCNN*, 2021 Int. Conf. Comput. Eng. Artif. Intell. (ICCEAI), pp. 281-285 (2021).
21. M. Priya, C. Ramakrishnan, S. Karthik, *Fetal 3D-echo classification and segmentation using color and textural features for TR detection*, Rev. Roum. Sci. Tech. – Électrotechn. et Énerg., **69**, *1*, pp. 109–114 (2024).