A Novel Optical Design Solution for Computer Vision-Based Automated Defect Detection in Textile Fabric Production.

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A novel optical design solution for computer vision-based automated defect detection in textile fabric production

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***Abstract*— The automated defect detection system on industrial manufacturing lines in today's diverse world of consumer goods is a necessary requirement. Quality control is performed at various stages of a large-scale production process, including raw material and pre-production material inspections, in-process quality checks during production, and quality control of packaging, labeling before market releasing.**

In many industries, such as the garment industry, the quality of input materials significantly influences product quality, material utilization ratios, and ultimately the profitability of manufacturers. Fabric is one of the most critical input materials in the garment industry. However, during fabric production processes such as weaving, dyeing, and packaging, numerous factors can affect the quality of the raw fabric. Various fabric surface defects may occur, including yarn loss, yarn breakage, single yarn or area shrinkage, uneven dyeing, inconsistent color distribution, mold spots, and fabric thread breakage. These defects directly impact the final product and need to be eliminated during the classification process before entering production.

Using manual labor to inspect each fabric roll with high accuracy becomes impractical in many cases due to several factors: experience, visual acuity, fabric roll speed, and psychological factors affecting operators' mental health from observing a monotonous surface for an extended period.

All of these factors lead to the necessity of an error detection system on surfaces such as fabric. In this research, we introduce an approach to an optical system aimed at observing and detecting deviations in the fiber structure using images captured from a monochrome camera and a lighting system designed based on the actual structure of several types of fabrics used as research objects.

***Index Terms* — Automatic Optical Inspection, Computer Vision, Illumination, Machine Vision, Optics.**

1 INTRODUCTION

IN the textile industry, product quality control is one of the most important requirements since textile is the material used in not only clothing but also in vehicle industry, filters in environment applications, construction… Each application gets their own quality requirements such as: color, surface defect or textile structure defects.

Numerous factors contribute to the occurrence of defects in textiles, including processes such as weaving, dyeing, and cutting. Additionally, defects can arise during storage due to conditions such as high humidity leading to mold growth or oil leakage from machinery components. That means in the realm of textile industry, fabric defects can manifest as regions exhibiting differential coloration on the fabric's surface or structural irregularities within the woven yarns, such as yarn misalignment, yarn breakage, or other forms of damage like tears, fiber protrusions, or surface abrasions. These imperfections can vary in size,

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Figure 1. Real horizontal size of roll of fabric (1560 mm).

Figure 2. Real surface of roll of fabric.

ranging from a few millimeters to several hundred millimeters, contingent upon the specific scenario [1-3].

Detecting small-sized defects within large field of view (Fig. 1) is quite challenging when dealing with the high-speed continuous rolling of fabric. In the case of larger defects, there are instances where even modest color contrast can impede ease of detection during visual inspection or examination with the naked eye within the production process. This challenge arises due to the substantial size of the observation area on each fabric roll, extending both horizontally and vertically. Furthermore, the human eye's capacity for sustained concentration is limited and is significantly influenced by the color characteristics of the object (Fig 2) [4].

Over the past several decades, automatic inspection systems have witnessed widespread adoption within mass production lines, employing a diverse array of techniques encompassing sensors, cameras, laser scanning, and more.

Machine vision systems employing digital cameras have seen widespread integration across multiple facets of modern production facilities. This technological advancement has ushered in a myriad of transformative capabilities, offering not only enhanced accuracy but also long-term stability to various inspection techniques [5-12]. Within this context, it is crucial to emphasize the paramount importance of meticulously managing the quality of input images, as this critical element plays an indispensable role in ensuring the reliability and efficacy of the entire inspection process [13-16].

However, the successful operation of these systems is contingent upon a fundamental prerequisite: the quality of input images. In essence, the efficacy of machine vision inspection hinges on the clarity, resolution, and reliability of the visual data it receives. Poorly captured or distorted images can lead to false positives or negatives, compromising the overall accuracy of the inspection process. Therefore, it's crucial to pay careful attention to optimizing the conditions under which images are captured, including lighting, focus, and camera calibration [17-20].

The quality of input images depends on the camera, optical lens, and the lighting system. The better the lighting system used, the more effectively it can highlight defects. This, in turn, improves the detection algorithms. Sometimes, issues like reflections from ambient light, uneven

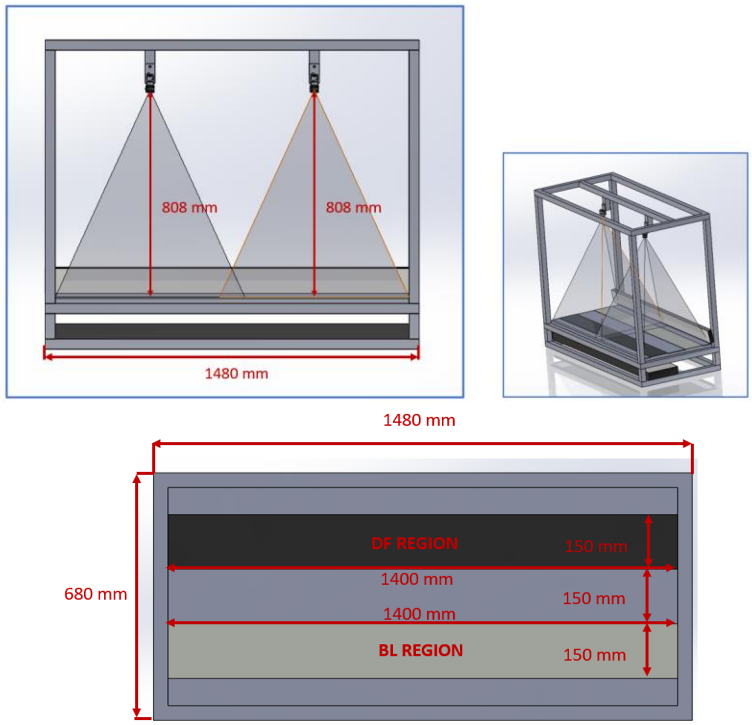

Figure 3. Real system and FOV of camera.

lighting across images, and the similarity between defects and normal areas can lead to errors. There are two types of mistakes that can occur: 'underkill' and 'overkill' [1, 6, 11, 15].

'Underkill' is when the system misses real defects, which can allow faulty products to be sold. 'Overkill' happens when the system wrongly identifies good products as faulty. Usually, factories want to avoid 'underkill' as much as possible, even if it means having some 'overkill.' That's why it's essential to design vision systems that can highlight unusual areas on objects [18-20].

For an optimized vision system design, engineers must acknowledge that a one-size-fits-all approach is not applicable. Factors such as the size, structural characteristics, material, and color of the object or the area to be inspected on the object must be taken into account and factored into the design calculations. In this research article, we have chosen fabric as the subject of our study.

Typically, a roll of fabric can have a total length ranging from 60 to 300 meters and a width that varies from 1400 to 1800 millimeters, depending on the supplier and the specific requirements of clothing companies. Therefore, the inspection area must cover the entire width of the fabric roll, and the inspection process occurs continuously along the length of the fabric roll as it unwinds onto standard rolls, preparing it for the cutting and subsequent stages in the production line.

Fabrics are usually rolled at speeds of approximately 10 to 30 meters per minute, with workers or automatic inspection system directly observing the fabric's surface to identify defects and their corresponding locations. Whether the fabric continues through the production process or not upon the detection of defects depends on the specific requirements of each case.

With the goal of detecting small defects ranging from a few millimeters to several centimeters in size, we propose a system using two cameras simultaneously. Each camera covers slightly more than half of the fabric's width. For fabric samples with a width of 1400 mm, we selected optical lenses and distances to the fabric surface to ensure that the observed area across the width is approximately 800 mm, as shown in Figure 3.

Nevertheless, it's worth emphasizing that this lighting system has been customized to meet the

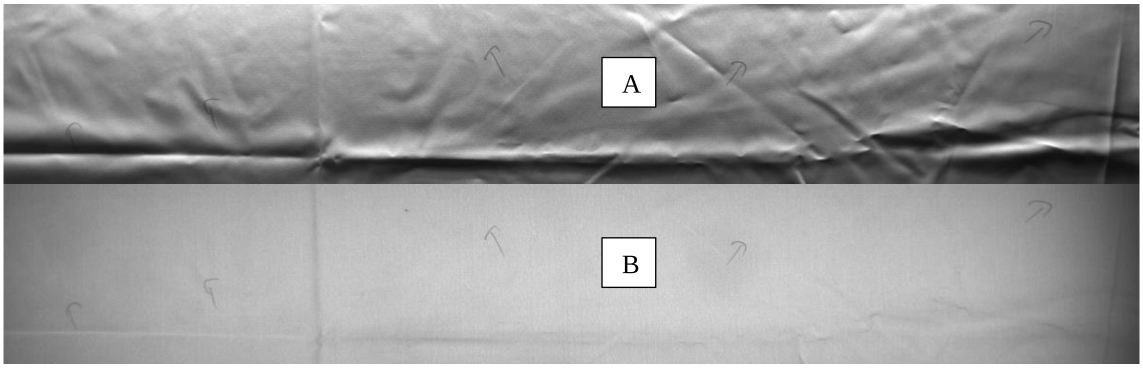

Figure 4. Real images of fabric under Back Light (A) and Dark Field (B) lighting system.

needs of simulating inspections within a controlled production line environment. In a real-world production line scenario, certain modifications and adaptations will be necessary to ensure that the system functions optimally under the conditions of the actual working environment. These adjustments might encompass changes to the configuration, intensity, or placement of the lighting, as well as potential additional equipment or technology integration. The goal is to seamlessly integrate this system into the practical processes and challenges of a real production line, maximizing its efficiency and effectiveness in enhancing quality control and inspection procedures.

2 Objects, System and Methodology

2.1 Objects

The optical system in this study was designed based on the analysis of the research objects, which consisted of dyed fabric samples prepared for the cutting stage and subsequent processes. With 91 fabric samples made from various materials such as cotton, elastic, and synthetic fabrics, and featuring a range of colors including black, navy blue, yellow, red, and white, the objective was to design an optical system capable of being used in a real production line.

Due to space limitations in the experimental conditions, we did not use fabric samples with a full width of 1400 mm. Instead, we designed a system with a field of view (FOV) just wide enough to observe more than half the width of the actual fabric (approximately 808 mm). To adapt it for use on a real production line, only an additional camera of the same type and a matching lighting system will be required to extend the observation area beyond 1400 mm in width, as illustrated in Figure 3.

Our inspection checklist includes defects such as **weaving issues, dyeing problems, cutting errors, mold growth, oil leakage, misaligned yarn, broken yarn, tears, protruding fibers,** snagged yarn**, and surface abrasions.**

2.2 System

Camera and lens. The image acquisition system in this article is taken using a 12M resolution digital mono camera (4024 x 3036 pixels) and a C-Mount 8mm lens with working distance 808 mm. The physical size of each pixel in digital camera using is 1.85 x 1.85 µm, the main field of view (FOV) for each camera in this system is 150 x 750 mm that can cover a haft of roll size. Mono image is used to avoid the affect of color of textile on contrast of defect in images [17-24]. Schematic diagram and real images of the system are shown in Figure 3.

LED and LED Controller. The lighting system has been designed using white LEDs with a power of 1W/LED (in continuous mode). While it is acknowledged that the use of white LEDs may introduce certain optical aberrations, notably chromatic aberrations at the image border, it's essential to weigh this against the practical requirements and goals of the current research endeavor. The choice of white LEDs is driven by the diversity of colors and patterns present in real-world fabrics used in sewing applications. This diversity is the reason why designing a monochromatic LED lighting system for fabric inspection using a digital camera is not feasible.

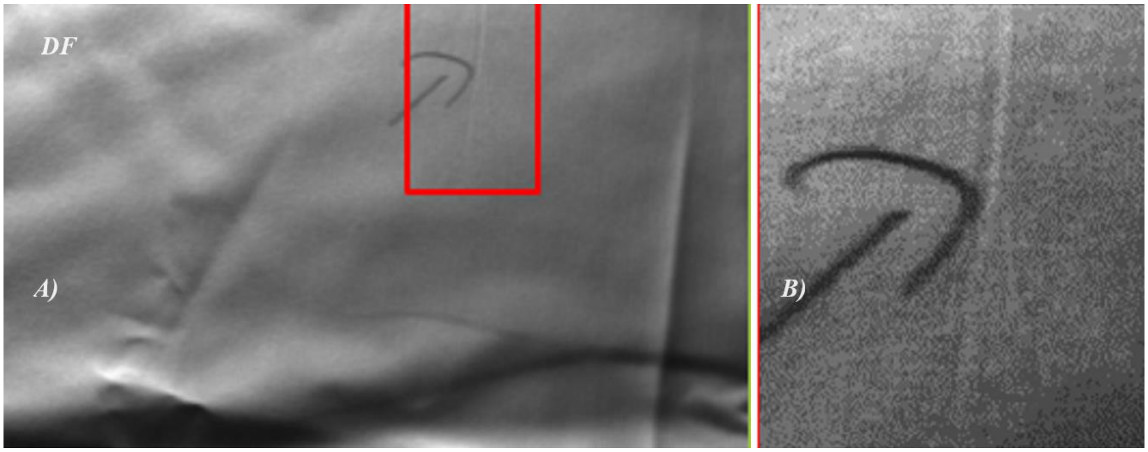

Figure 5. DF Image of textile with surface deformation defect (A) and zoom-in defect area (B).

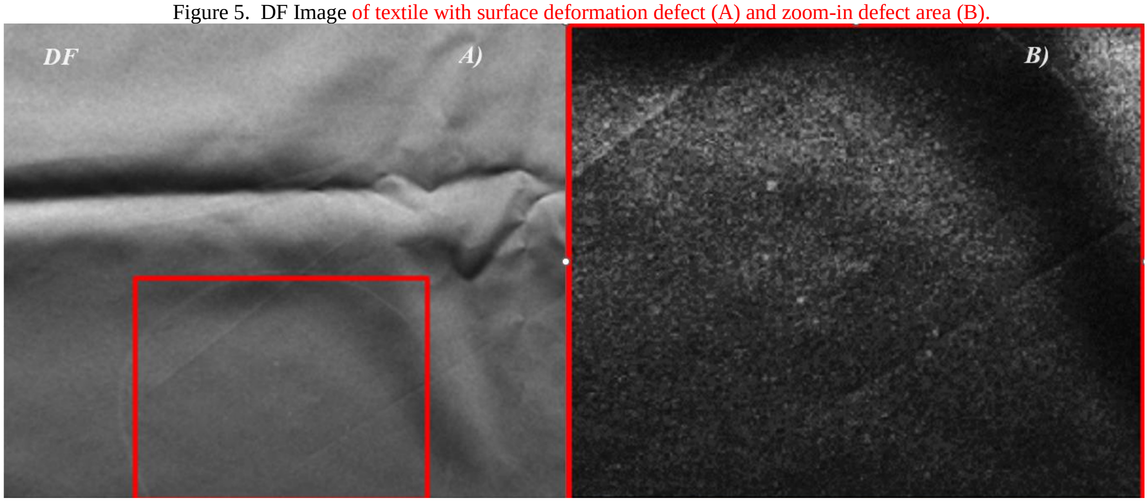

Figure 6. DF Image of textile surface with color dot defect (due to dying process).

Therefore, the use of white LEDs is the most logical and sensible choice for this specific application. It is crucial to emphasize that this decision aligns with the overarching objectives of this research, which is to create a practical and efficient fabric inspection system capable of accommodating the diverse and complex array of textiles found in real-world manufacturing settings.

To control the lighting, we use a 48V LED controller that regulates the current instead of voltage. This controller ensures that the lighting remains stable during long working periods. It can be adjusted for output current, pulse width, and trigger delay time as needed. The pulse width matches the camera shutter speed, reducing LED active time, minimizing heat, and extending the LED lifetime.

2.3 Illumination Lighting Method

Based on checklist of defects the illumination lighting method we consider using is Dark Field (DF) and Back Light (BL).

The Dark Field lighting technique is a method used in many observation systems. Light is directed towards the observed area at a low angle to ensure that the reflected beam of light does not travel directly into the observation axis (in the case of observing with a camera and lens, the reflected beam of light does not enter the optical axis of the lens). In this setup, under observation, the observed surface appears unilluminated. This means that if it's an ideal flat surface, the observed image will have an ideal dark area. When the surface has irregularities (scratches, dents, punctures, dents, etc.), that area becomes a region of scattered light, and the scattered light has many directions of propagation. Some of it will enter the observation

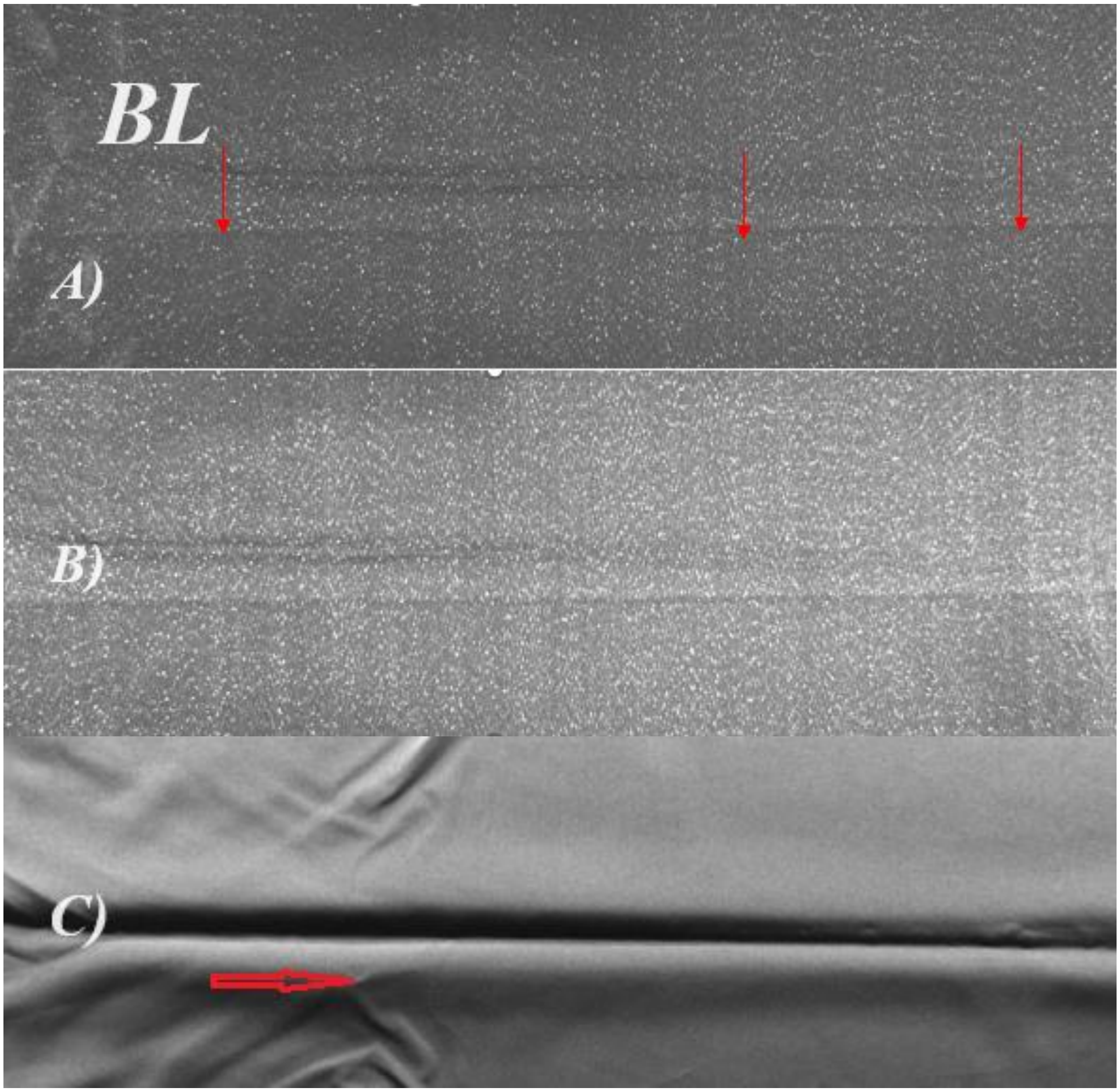

Figure 7. Raw BL Image (A), BL after processing (B) and DF Image (C) of textile with structural yarn defect.

area (or enter the optical axis of the lens in the case of camera and lens observation) to create an image. The brightness of the scattered region on the image will vary depending on the specific structure of that area. However, when observed against a dark background, only a moderate intensity of light is needed for that area to stand out prominently and be easily observed or detected. However, the drawback of this method in quality inspection for soft surfaces such as fabric is that wrinkles or surface protrusions (which are not defects) will also appear in the image with a relatively high contrast compared to flat fabric areas. This can pose some challenges for the development of image processing software to detect defects later on (Figure 4A). To avoid this, we propose using a second technique, which is backlighting the fabric panel from behind (Back Light).

Backlighting is a lighting technique designed for transparent or such material of objects that allow some light to pass through. If the observed sample has different structures within its composition, light absorption will vary in those areas, creating contrast in the image between normal and abnormal regions. For thin structures like textiles, minor wrinkles or non-flat surfaces caused by the fabric rolling process typically have minimal impact on brightness, ensuring that the observed image is not distorted when detecting defects. However, the drawback of this method is that

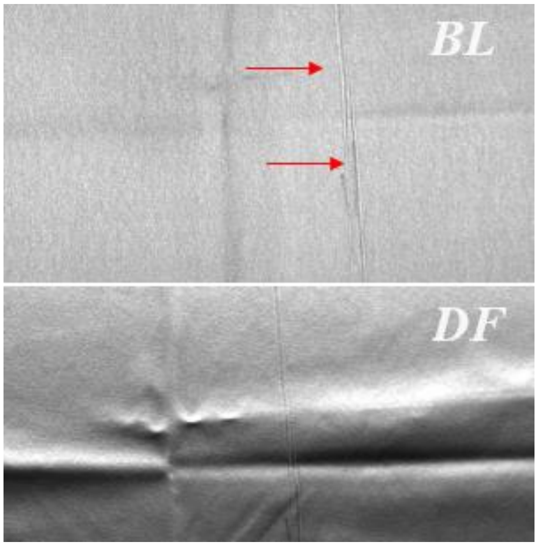

Figure 8. Raw BL Image, and DF Image of textile with structural yarn defect.

image details may not be as sharp as with other lighting methods because when light passes through the fabric surface, it scatters across the fabric fibers and different structures, creating various directions of light for the observer or camera. Nevertheless, significant anomalies within the underlying fabric structure will exhibit an acceptable level of contrast compared to normal regions. This can aid image processing and the detection of these abnormal areas without being influenced by the flatness of the fabric surface (Figure 4B).

3 RESULTS

The fabric surface is a scattering surface with numerous multi-directional structures of fabric threads; hence, the obtained images cannot have the sharpness and contrast levels seen when capturing images on plastic or metal surfaces. However, with a design using DF and BL techniques, the images obtained in the anomalous regions still have enough contrast for use in subsequent image processing algorithms. In the case of surface defects like deformations (Fig. 5), we can see that the DF image clearly shows the contrasting abnormal region against the normal fabric background after applying a simple contrast enhancement algorithm (Fig. 5B). For defects such as ink spots or unusual color spots (which may result from oil stains or mold), the images also exhibit contrast after a preprocessing step (Fig. 6 A, B). In these cases, when examined in the BL

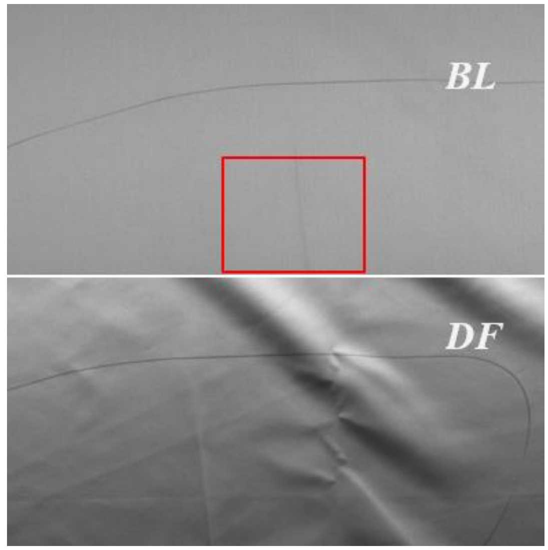

Figure 9. Pull or Snag defect images on BF and DF lighting techniques.

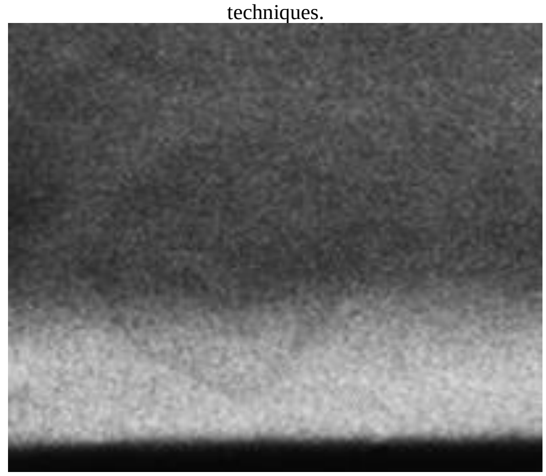
Figure 10. DF image of oil leaking on fabric surface.

image, the difference is sometimes not significant because these color spot layers are often very thin, and the light absorption in that area may not be sufficient to create the necessary contrast for algorithms to detect them without being affected by image noise.

In thin and stiff fabric types, structural damage is quite challenging to detect in DF (Darkfield) images because the light from the DF system primarily scatters from the fabric's surface. The folds or creases in the fabric roll also pose significant difficulties in identifying the abnormalities in the fabric fiber structure (Fig 7C). However, when using the BL (Brightfield) images, these structural abnormalities exhibit a certain level of contrast compared to the surrounding structures (Fig. 7A), and with a contrast enhancement processing step, these irregularities

Defect type	Qty	Highlighted	Percentage (%)
Dot defects (color, oil leak, dirty)	19	16	84.2
Yarn defect (snag, pull)	25	22	88.0
Yarn structural defect	19	12	63.2
Abnormal color area	7	3	42.9
Tears, cut, dent appear on surface	21	17	80.9

Table 1: Result of defect highlight on optical system.

become more apparent (Fig. 7B). This contrast level varies among different fabric types; therefore, assessing the capability to detect this type of defect will require more time and a larger sample of defective products to evaluate the detection rate for this type of defect.

Other types of fabric structural defects, such as missing or misaligned fabric yarns, if large enough to appear both inside and on the fabric surface, can be easily observed in both lighting techniques (Fig 8). However, in the case of BL (Brightfield) technique, the images exhibit more stable surface brightness, making detection quicker and more accurate. Nevertheless, for surface imperfections like fabric pulls or snags, although their structure is still distinguishable in BL images, only in DF (Darkfield) images can we conclusively identify the specific type of defect (Fig. 9). This is quite significant for categorizing and storing defect data, as it leads to data analysis and improvement of fabric preparation processes at specific stages, aiming to minimize the occurrence of defects in the production process.

For defects such as oil leaking or surface stains on the fabric, detection is almost exclusively achievable through the Darkfield technique (Fig. 10). This can be attributed to the fact that thin layers of dirt or oil, if present, absorb very little light from the Brightfield system, making them indistinguishable from the surrounding areas. However, due to their location on the fabric's surface, these areas will scatter light differently from the surrounding regions. As a result, in the images, these defect's areas will also appear relatively distinct and can be effectively utilized for image processing algorithms.

We conducted an image collection on 91 samples of various categorized defects grouped into 5 main types. The proportion of samples that could be highlighted is illustrated in Table 1 through statistical analysis of the highlighting capabilities of both the Brightfield (BL) and Darkfield (DF) lighting techniques.

In the case of abnormal color area defects, the proportion of samples with detectable highlights was rather low (42.9%), similarly, yarn structure defects showed an unfavorable highlighting rate with the optical system under design while other defect types exhibited highlight rates exceeding 80%.

4 Conclusion

These results also underscore the current limitations of these two techniques in classifying and detecting defects in a large field of view, influenced by factors such as color or fabric structure. Although 3 out of the 5 main defect types exhibit highlighting rates, the results for the remaining 2 defect types with excessively low highlighting rates pose a significant limitation for the practical application of this optical system. To meet the real-world requirements of automated systems, this optical system will need further refinement and improvement in future research endeavors.

Conflict of Interest. The authors declare that they have no conflict of interest.

5 Acknowledgement

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHOR CONTRIBUTIONS:

Sy Hieu Dau, Le Nguyen An Khang and Tran Minh Thuan contributed to the optical system design and image data collection of the specimen.

Dang Thi Phuc contributed to image processing and verification.

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