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IE 423

Quality Engineering

Project Part 3 Report

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Introduction

Linen, a textile derived from the flax plant, stands out in the manufacturing landscape despite its higher production cost, owing to its desirable qualities such as strength and superior absorbency compared to cotton. The intricate process of linen manufacturing, however, introduces potential defects arising from both assignable causes like machinery issues and yarn problems, as well as random factors like needle misplacement.

The historical significance of linen, with roots dating back nearly thousands of years, showcases its versatility in applications ranging from clothing to canvases. Acknowledged as a luxury item, linen's pricing, seemingly higher than other textiles, gains clarity upon analyzing its production process. Detecting defects during linen production is paramount, as it directly impacts the quality of the final product. Timely identification allows for more straightforward and cost-effective problem resolution, a critical aspect given the higher expense associated with linen.

Identifying defects, however, poses challenges, as they are often too small to be noticed through manual inspection alone.Manual inspection, prevalent before the rise of image processing and computation power, had limitations, with even the most skilled fabric inspectors identifying only up to 30% of defects. This prompted the adoption of image processing and other technological techniques to automate and enhance the efficiency of quality inspection in linen manufacturing. So, the motivations behind employing advanced imaging techniques and defect identification in linen production stem from the industry's pursuit of enhanced efficiency, quality assurance, and sustainability.

Background Information

The inspection of linen fabrics involves diverse methods, with structural, statistical, spectral, model-based, learning, and hybrid approaches being prominent. Structural methods, relying on textural primitives, are less reliable for irregular patterns, while statistical approaches like co-occurrence matrices face computational challenges but offer high accuracy in detecting defects. Spectral approaches, including wavelet transform and Gabor transform, vary in efficiency and computational cost, with Gabor transform being adaptive but computationally demanding. Model-based approaches, such as AR models and Gaussian Markov random field models, focus on relationships between pixels but are more sensitive to noise. Learning approaches, requiring substantial data, are effective but computationally complex. Hybrid approaches, combining various methods, enhance accuracy, and comparison studies emphasize the need to tailor methods to fabric and defect types.

Multivariate image analysis (MIA), Wavelet Texture Analysis (WTA), and Gray Level Co-occurrence Matrix (GLCM) are widely used for automated vision in textile processes. MIA applies PCA to spectral signatures for defect monitoring, while GLCM, relying on second-order statistics, is computationally affordable. WTA outperforms other transform-based methods, leveraging wavelet transform for fault detection. The existing methodology in textile involves manual inspection, prone to human error and inefficiencies. Digital systems utilizing image processing techniques offer a more reliable and efficient approach to defect detection, as demonstrated in various studies.

Defect detection in textile production faces challenges due to machine failures, material defects, and poor finishing. Automated methods, such as image processing in MATLAB, offer efficient fault processing. Zhang and Bresee compared image analysis techniques for recognizing faults, emphasizing the efficiency of statistical methods over morphological operations.

Approach

During our research, we found that a type of image transformation technique named Gabor filtering was used in fabric defect detection systems and it increased the success of these systems.[1] Although there are advanced algorithms used in these defect detection systems, the success chances of simple algorithms are also increased by Gabor filtering.

We applied Gabor filtering to our image with several different parameters. For each filtered image we tried the following:

We calculated the mean and standard deviation of each row and column. Then, we found the mean of all pixel values and average standard deviation for rows and columns. According to these values, we calculated control limits according to the formulas in the table provided in Moodle. After that, we checked each row and column with respect to these control limits. If the row/column was out of control limits, all the pixel values in the row/column were changed to 0. However, this turned out to be unsuccessful because most of the lines and

[1] Kim, J., Jo, H., Ri, J. *et al.* Automatic fabric defect detection using optimal Gabor filter based on hybrid beetle antennae search–gravitational search algorithm. *J Opt* **52**, 1667–1675 (2023). https://doi.org/10.1007/s12596-023-01126-9

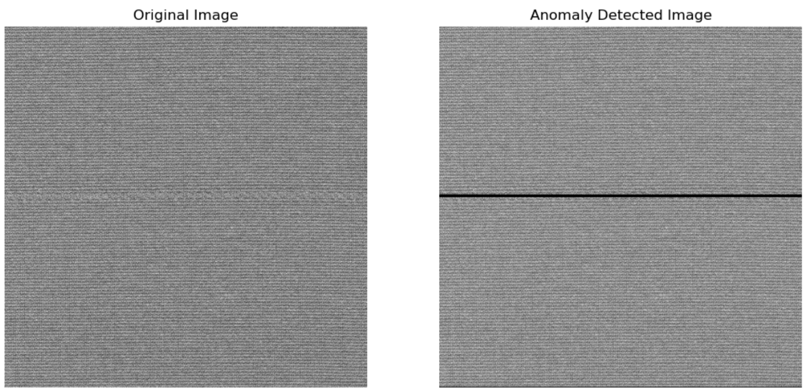
columns were found to be out of control. We found that control limits calculated according to the formula were too low and assigned a fixed multiplier value to control limits, 1. When lambda was 12, theta was 90, and bandwidth was 8, we successfully found the defect in our image. When we applied the same algorithm to other images, we were usually successful in images that resembled our image (images with whole rows or columns of defects). However, when the defect was scattered in different parts of the image, the algorithm was unsuccessful. It either didn't find the defects or made the whole row/column black when the defect was in just a part of the row/column. In order to prevent this, we needed to work on smaller samples, not whole rows or columns. We divided each row and column into parts. Each part consisted of 8 pixels. After that, we made control limit calculations according to these parts and ran defect detection functions. We found that this approach was unsuccessful. It couldn't find some defects and it had a large type 2 error. That's why we decided to split the image into squares and detect defects in these squares. This approach would increase the number of elements in each sample, therefore decreasing variability, and it would also be useful for finding small defects in some parts of rows/columns without marking the whole row/column. To find the optimal square size, we split the image into squares of side size 2, 4, 8, and 16. After that, we tried the method written below for each side size and concluded that side size of 8 would be the best choice. When the side size was 2 or 4, both type 1 and type 2 errors were larger than side size 8. When the side size was 16, we expected a decrease in type 1 and type 2 errors again, but the outcome was different. The type 2 error increased because the squares were large and non-defective places were also marked. To fix the issue, we iterated through each pixel in the marked zone and if the individual pixel was in control limits (calculation of control limits are explained in next paragraph), we didn't change its value. However, this approach didn't work as expected and didn't improve the results. Therefore, we decided that squares with side size 8 (sample size 64) was the best choice.

We calculated the mean and standard deviation for each square. After that, we calculated the average mean and average standard deviation. According to these values and formulas in the table provided in Moodle, we calculated control limits. Then we checked each square with respect to these control limits. If the square was out of control limits, the pixels in the square were assigned 0. We found that this algorithm had marked a lot of squares as defects and multiplied the control limits by 3. This time, the algorithm couldn't find the defects in our image and images that resemble our image. However, it was successful in finding defects in other images that had defects scattered in several parts of the image. That's why we decided to use both algorithms. However, we quickly found out that, when both algorithms were used, type 2 error was very high. So, we decided to first use the square method. If the number of pixels marked as defected were less than 1% of all pixels, we concluded that the method was unsuccessful in finding defects and used the row/column algorithm. This decreased type 2 error but increased type 1 error. However, it was the most successful among alternatives that were tried before.

Results

The baseline defect detection approach and the use of different control charts could not successfully detect defects in the selected image due to the different structure of the pixel data from 1D regular data. In our approach, we utilized a Gabor transform and tested it on six different images, including the initially selected one.

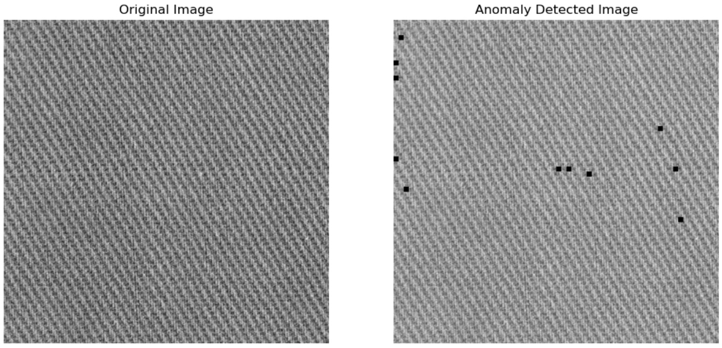
The result of the initial image is as follows:

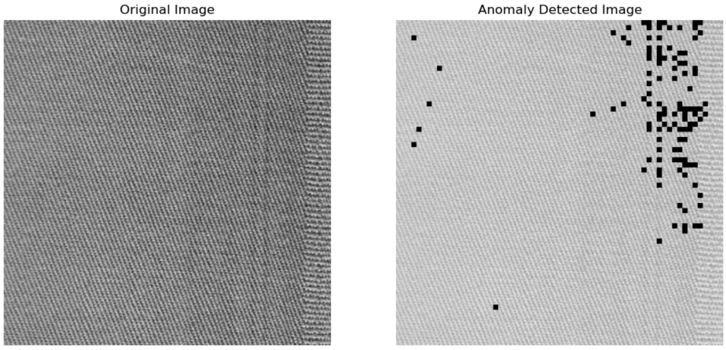


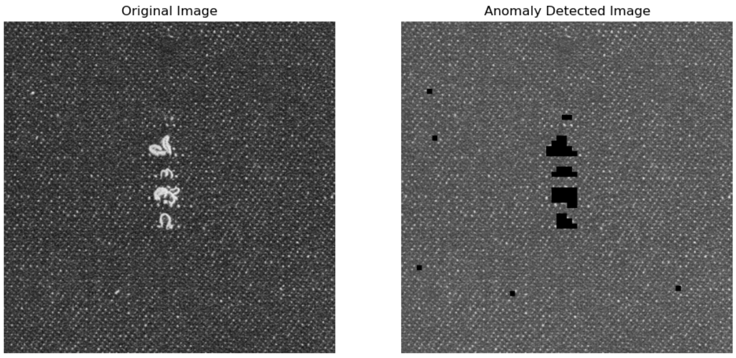
Our approach performed successfully in the original image, accurately detecting the defective parts.

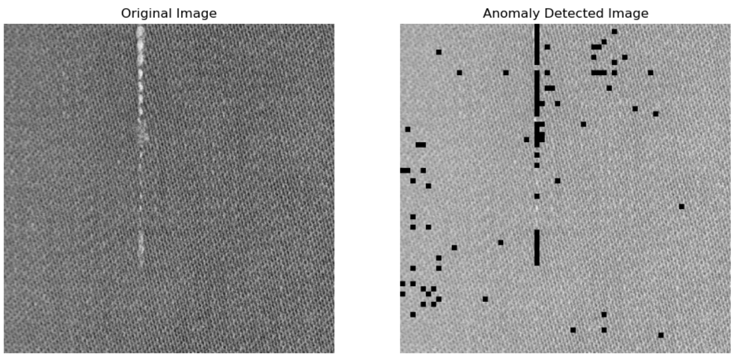
However, for some other images, it occasionally produced false signals, indicating that it might not be as efficient in detecting different layout patterns. These images exhibited different defect patterns, with some laying out horizontally, some vertically, and others having neither pattern.

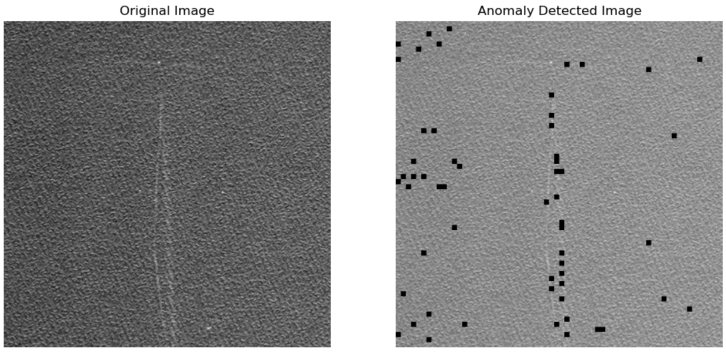
The results of the alternative images are as follows:











Despite some false signals and some undetected defect parts, it is evident that our approach is much more efficient overall compared to the initial two approaches that failed to detect defective parts.

Conclusions and Future Work

In conclusion, classical statistical control approaches do not work well with image defect detection due to the spatial pixel data and correlations, despite our attempts with different control limits and charts. Through research in the field of image defect detection, we discovered numerous methods and approaches. Among them, we chose to implement the Gabor transform. The Gabor transform is a challenging concept, and selecting appropriate parameters can be a difficult task. After trying various parameters based on our original image and its horizontally oriented defects, we identified the parameters that yielded the best results.

While our approach excels in detecting defects in our specific image, its efficiency might decrease when applied to images with different defect shapes. To enhance our method further, we can explore alternative parameters and control limits. Additionally, we can check more images to increase the accuracy of our results.

References

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