IE 423: QUALITY ENGINEERING

PROJECT PART 3

QUALITY CONTROL ON IMAGES

YUSUFCAN ÖZKAN 2019405105
SUDE YILMAZ 2019402054
Group ID: 19

INTRODUCTION

Linen is a natural textile produced from the fibers of the flax plant. The importance of monitoring the processing of linens comes from the unique nature of linen manufacturing. Linen undergoes a series of complex processes. Any deviation or defect in these processes can significantly impact the final product's quality. As the demand for high-quality linens continues to rise, the need for effective monitoring of the processing of linen fabric becomes important.

Integrating image analysis into linen manufacturing processes provides several benefits. Firstly, it enables a more efficient quality control mechanism. Secondly, as the textile industry undergoes a shift towards smart manufacturing and Industry 4.0, the incorporation of image-based technologies suits the trend of automation and data-driven decision-making. Real-time monitoring and analysis of linen fabrics through image processing not only enhance the overall efficiency of manufacturing processes but also contribute to the reduction of waste by identifying defects.

In summary, the monitoring of linen processing through image analysis is a crucial step in maintaining the quality of linen fabric. By implementing advanced technologies, manufacturers can elevate their production standards.

BACKGROUND INFORMATION

There are a variety of techniques to control the quality of fabrics by employing diverse methodologies, ranging from data mining algorithms to advanced machine learning and image processing techniques, to address the critical issue of fabric defect detection.

The integration of data mining algorithms is a promising approach for improving the accuracy and efficiency of fabric defect detection. By utilizing decision trees, clustering, and classification techniques quality control mechanisms can be obtained. Developing a model by training it with various datasets and then analyzing the objected fabric to detect defects is a developing approach. [1]

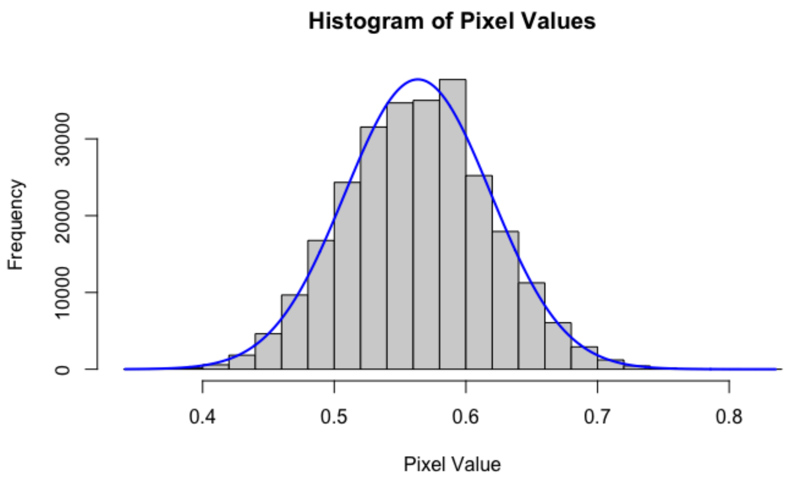
Another approach in the matter of the subject is using Convolutional Neural Networks (CNNs). This approach, rooted in image recognition, employs CNNs to automatically detect and classify defects. The use of deep learning models reflects a shift toward intelligent, automated systems that are able to realize real-time quality control processes in textile manufacturing.[2]

However, traditional quality control methods have been challenged by the unique characteristics of linen, leading to a demand for innovative approaches. The incorporation of image analysis in quality control, as observed in other materials with textures, has been recognized in the literature. However, existing research highlights the limitations of conventional control charts designed for 1D time series data when applied to 2D spatial data, such as images. The need for specialized strategies to address the spatial correlation in pixel values, especially in textured images, remains a focal point.

APPROACHES

1.1 A Baseline Defect Detection Approach from a Statistical Data Analysis Perspective

The pixel value distribution in the image through the construction of a histogram is examined to understand the overall distribution pattern. The probability distribution that closely matches the shape of the histogram is determined to be a Normal distribution. Related parameters are estimated by calculating the mean and standard deviation of the pixel values.



Assuming the pixel values conform to the selected distribution with estimated parameters, pixel values that are out of upper and lower bounds that enclose a 0.001 probability are decided to be marked as defects. Marked pixel values are set to the value of zero, to effectively detect those defects visually on the image.

1.2. Local Structure Analysis on Image Patches

The approach extends its application to image patches to analyze the image locally. By repeating the earlier steps for each patch, the method accounts for localized variations. The window size, which is 51x51, affects the level of detail of the analysis, emphasizing the relevance of considering local characteristics in defect identification.

This approach provides a structured and iterative methodology for defect detection, integrating global statistical analyses with localized assessments. By combining histogram analysis, parameter estimation, and outlier identification, the approach strives to enhance the precision and adaptability of defect detection in images, offering valuable insights into both global and local features.

2. A Simple Defect Detection Approach from a Control Chart Perspective

The methodology involves monitoring the mean and variance of each row and column, making the implicit assumption that the distribution of pixels should be consistent both horizontally and vertically.

2.1. Row-wise Quality Control:
Construct charts to monitor the mean and variance for each row of the image. In each individual row, identified pixels that deviate from the established control limits indicate an "out of control" signal. Control limits are decided to be 3-sigma above and below the mean.

2.2. Column-wise Quality Control:
Similarly, construct charts to monitor the mean and variance, applying control limits to identify pixels that are out of control in each column.

The emphasis on monitoring the mean and variance in each direction allows for a more comprehensive understanding of potential anomalies in the image matrix.

3. Proposal: Monitoring Autocorrelation Mitigated Control Chart for Image Quality Control

The provided approach involves adapting statistical process control techniques to the spatial nature of linen images. In pictures with textures, pixels may yield a high correlation with each other. Therefore, to apply a control chart approach, pixel values should be independent of each other. The utilization of a 2D moving average, as demonstrated in the provided code (refer to Appendix A), aims to smooth spatial data while considering both rows and columns. By normalizing and introducing control limits based on the statistical properties of the image data, we aim to identify and highlight regions in the linen images that deviate from expected patterns.

The code addresses the challenge of applying traditional statistical process control methods, designed for 1D time series data, to 2D spatial data in the context of image analysis. In traditional control charts, observations are typically made along a sequence (1D), but images present a spatial data structure (2D). The goal is to devise a control procedure that can identify problematic regions within an image using statistical process control.

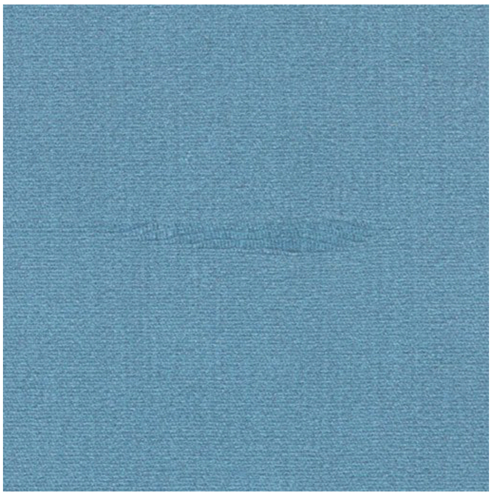
The MovingAverage2D function is crafted to enhance the analysis of spatial data, such as images, through the application of a 2D moving average. The code employs a two-step process: smoothing along rows and columns. During the row-wise operation, the function iteratively adds a shifted version of the matrix to itself, effectively replacing each element with the average of itself and its right neighbor. This process is then repeated for columns, where the matrix is augmented with a shifted version below, smoothing the data vertically. Normalization steps are incorporated to prevent bias, with the matrix divided by parameters lag_row and lag_col after each operation. The resulting matrix, MA, represents a spatially smoothed version of the original data.

In short, the code exemplifies an approach to adapting statistical process control techniques for 2D spatial data, addressing the limitations of traditional control charts built for independent 1D time series data. By introducing a 2D moving average and subsequent statistical adjustments, the code aims to enhance defect detection capabilities in images, particularly those with textures where pixel values exhibit spatial correlation. This strategy provides a foundation for devising effective control procedures tailored to the unique characteristics of image data.

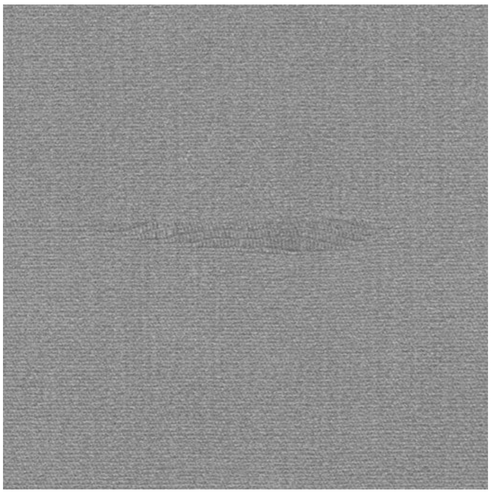
RESULTS

Objective Image: 0095.jpg

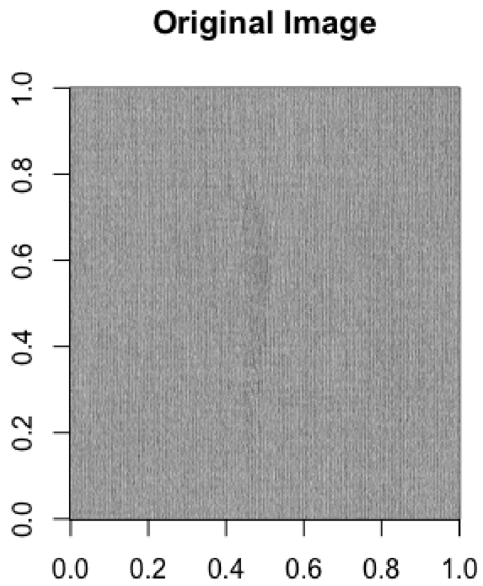
Objective Image:

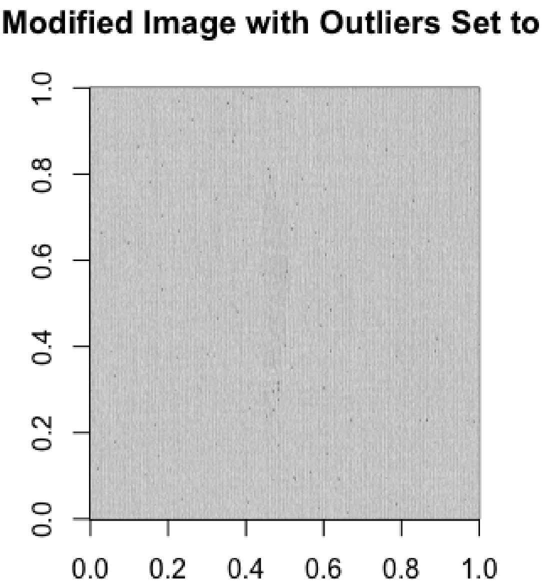


Grayscale Version:



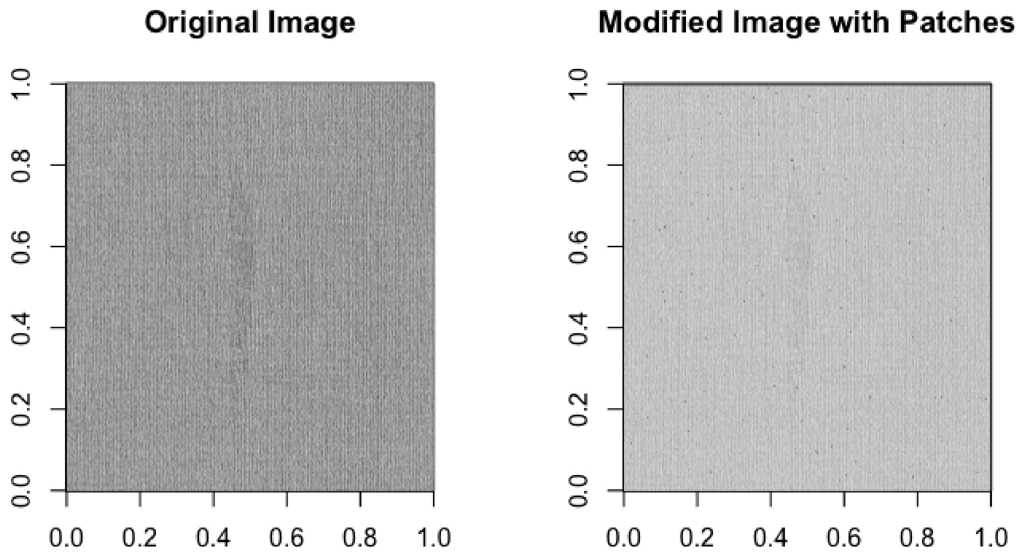
Results of 1.1st Approach: Statistical Data Analysis





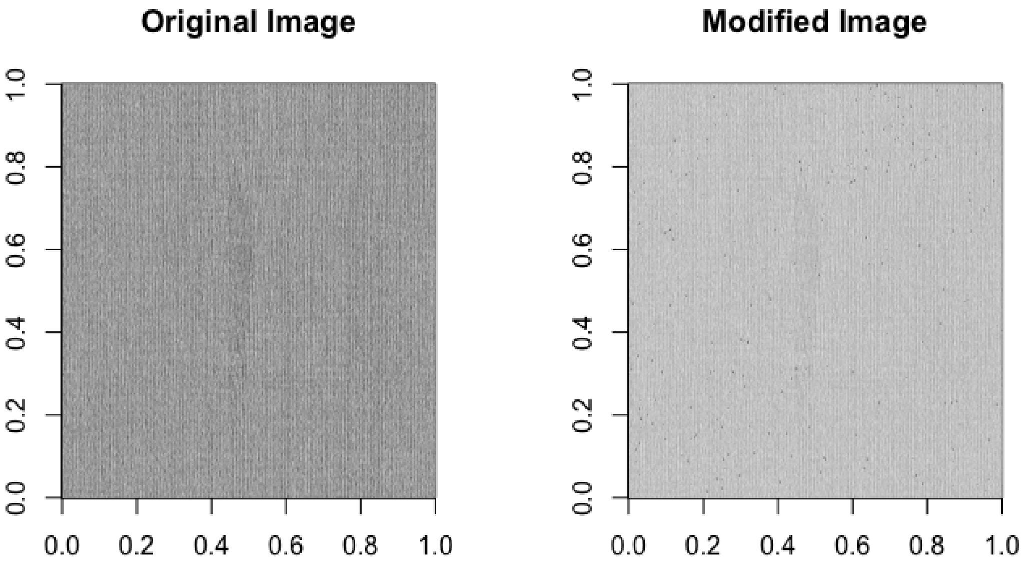
Modified image yields defective points that are all over the image. There is not a single pattern or region that outliers show. The method was not able to identify the actual defective region and also gave false alarms in terms of signaling at non-defective regions.
The number of defective points found with this method is 300, which is too less considering this is an image with 512*512 = 262144 pixels. Therefore, not a good and accurate result in terms of determining out-of-control pixels.

Results of 1.2nd Approach: Statistical Analysis on Image Patches



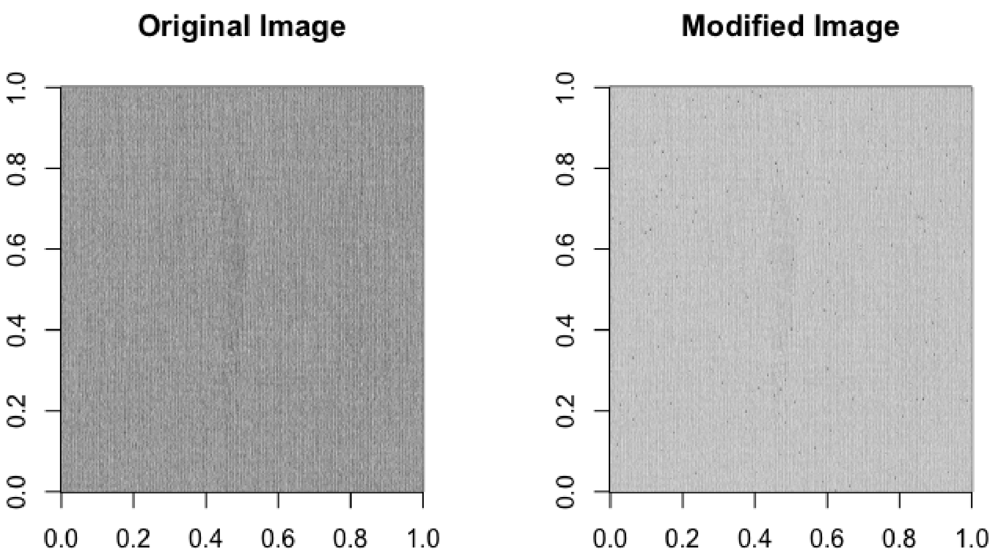
When the same method is applied to the image patches, the result changes by a very small amount. Still no accurate representation of the actual region of defects, but it yields a higher number of defective points. Therefore, if this would not be an image with texture, in a context with no correlation effect, this approach could be more sensitive to detect the defects. However, in this case not a successful result.

Results of 2.1st Approach: Row-Wise Control Charts



Considering each row separately and monitoring the pixels with a control chart allow us to monitor the mean and variance of the pixel values with the assumption that within each row distribution remains the same. There are a few signal points that are actually on the defective region, but this does not seem like the actual accuracy of the model, since again the out-of-control regions happen to be on every part of the image.

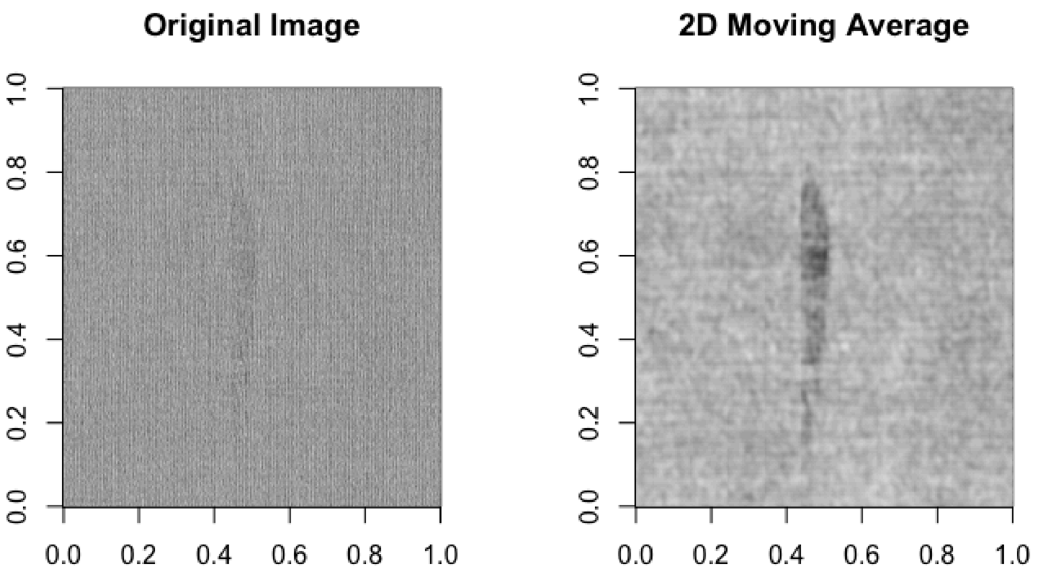
Results of 2.2nd Approach: Column-Wise Control Charts



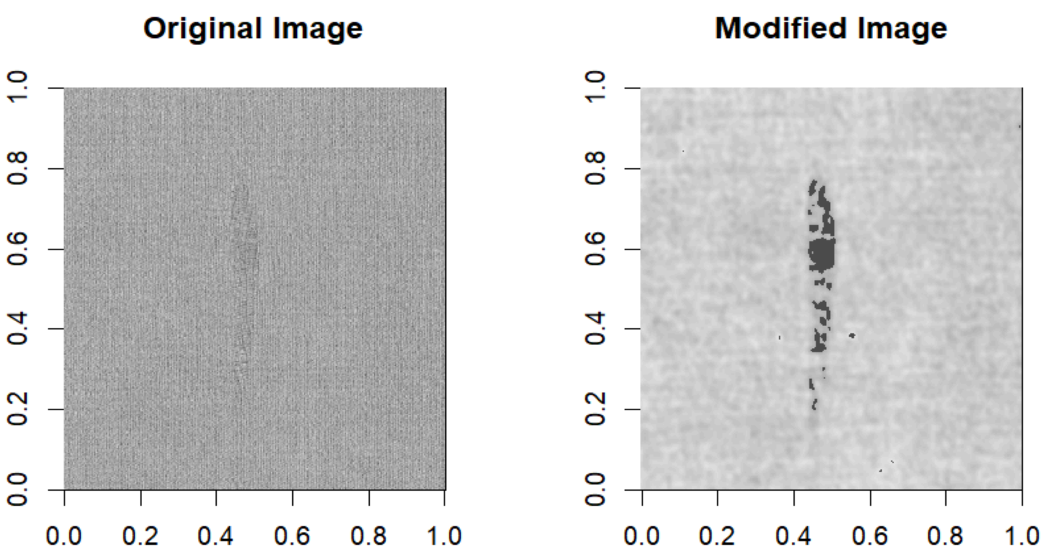
Similarly, considering each column separately and monitoring the pixels with a control chart allow us to monitor the mean and variance of the pixel values with the assumption that within each column distribution remains the same. However, again there is no successful result that accurately shows the defected region.

Results of 3rd Approach: Proposal of Monitoring Autocorrelation Mitigated Control Chart

Smoothed image using a 2D moving average:



Modified image after implementing control chart to smoothed image:



The results, presented visually, showcase the impact of the 2D moving average and subsequent adjustments on linen images. Comparison between the original and modified images illustrates the effectiveness of the proposed approach in highlighting potential defects. Statistical control limits provide a quantitative basis for identifying irregularities, particularly in areas where pixel values exhibit significant deviations.

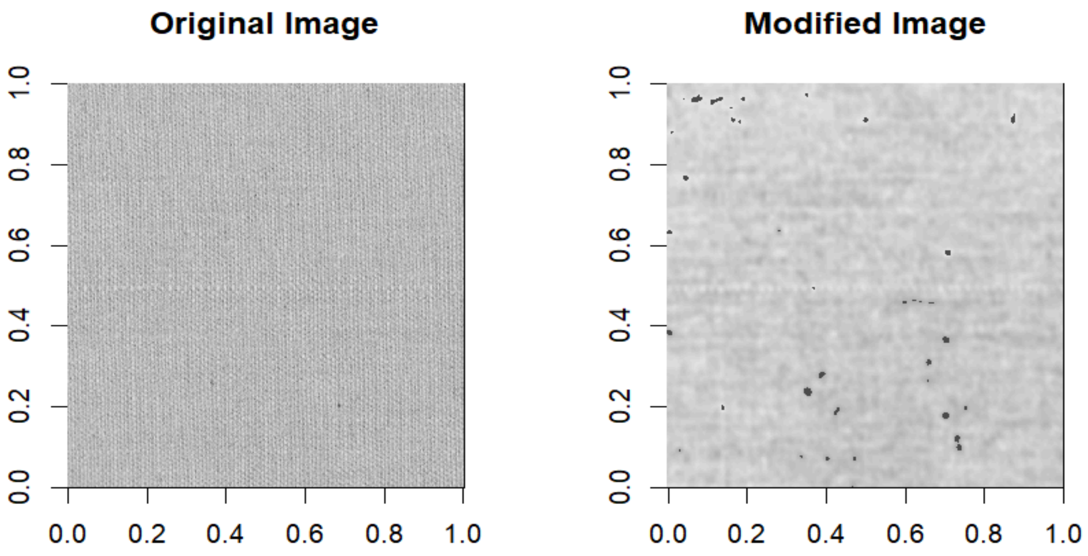
Comparison of Implementation of Proposal to Other Images

R generated 100 random integer (with seed value of 423) is provided below:

34 85 101 123 27 172 81 77 127 76 90 3 11 58 57 37 119 187 175 11 36 6 6 113
144 103 78 162 161 66 79 68 144 164 85 142 174 25 78 37 70 49 146 29 3 102 7
131 129 121 28 188 152 6 65 5 119 125 102 14 188 49 173 93 147 103 155 142 21 156
163 132 36 188 182 11 40 113 4 34 154 136 106 143 177 26 43 88 133 98 78 67 63
175 71 114 152 63 137 170

First 5 available images and their modified versions are shown below.

Image 27:



Unfortunately, for the Image 27, our approach did not perform as well as it did for the main image.

Image 34:

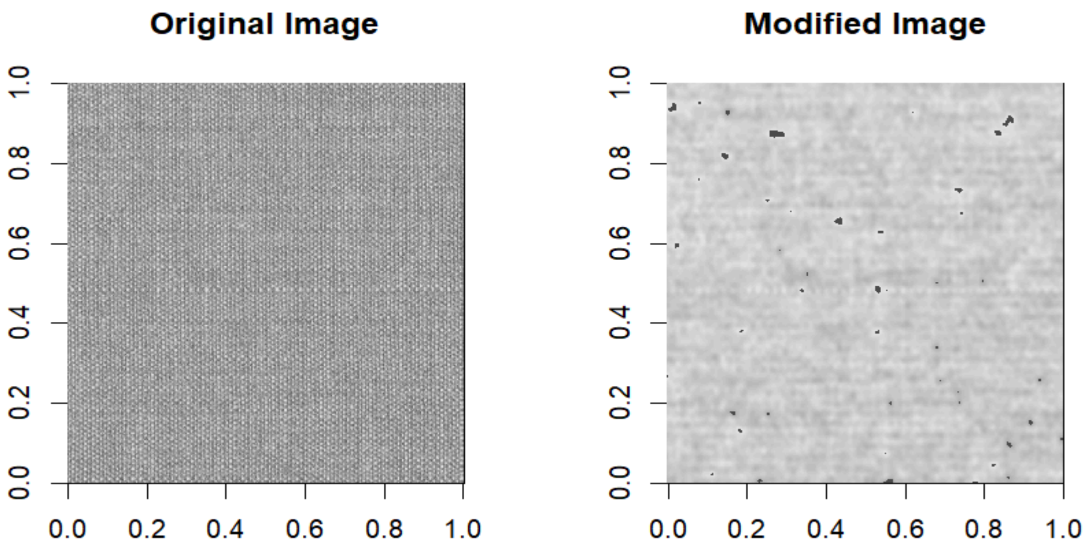
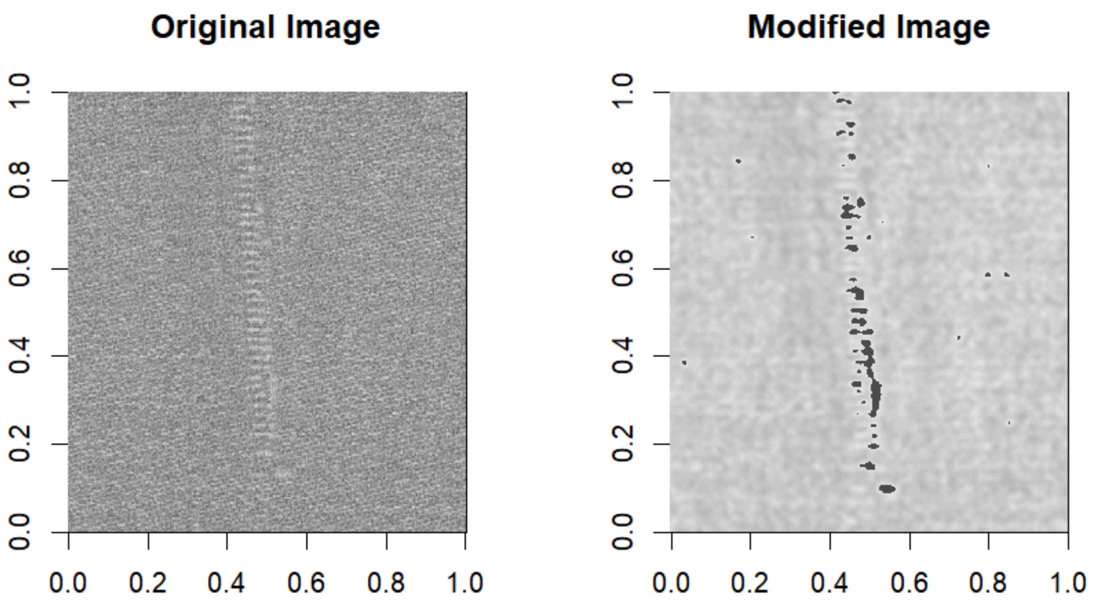


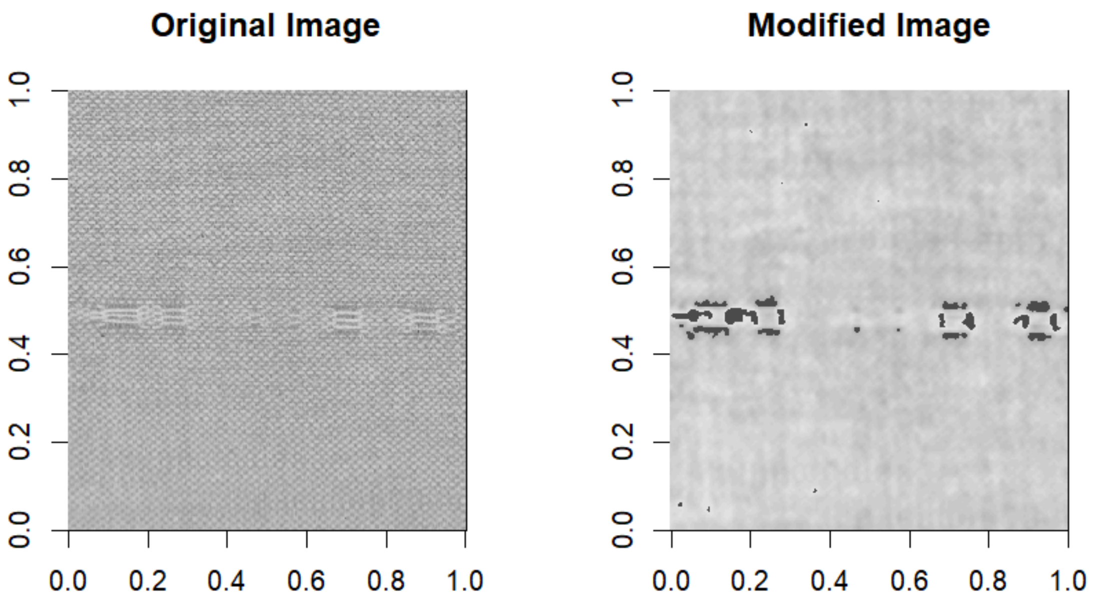
Image 34, which is very similar to image 27 also did not yield adequate results. From these two results, it can be seen that our approach does not perform well for thin line shaped defects.

Image 77:



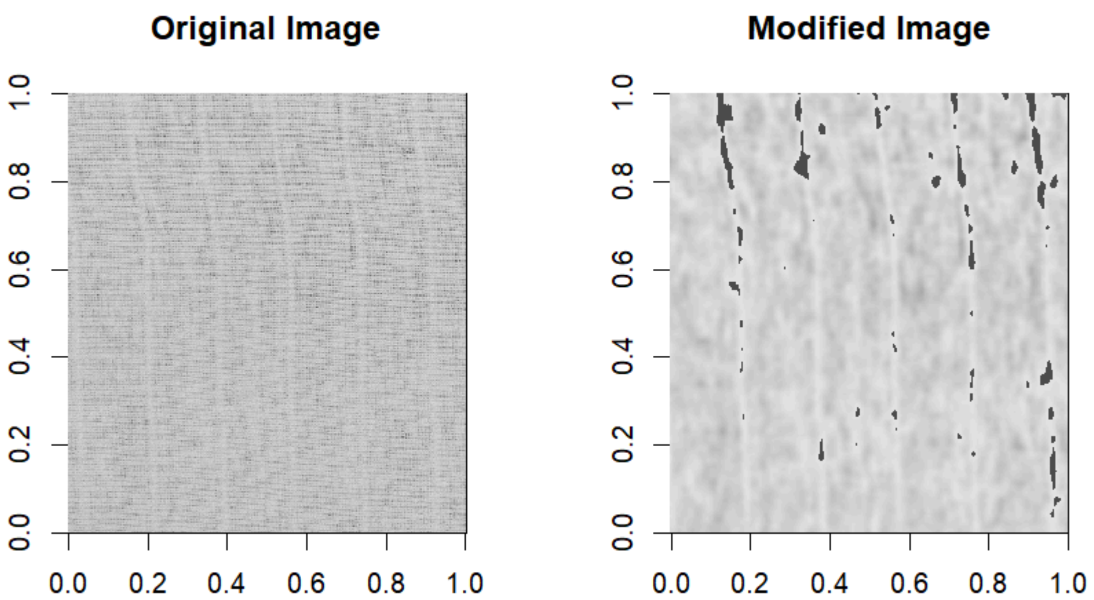
For the Image 77, our approach seems to capture the main defect. The result is significantly better than the first two comparison images.

Image 85:



For the Image 85, our approach seems to capture the main defects. The result is significantly better than the first two comparison images.

Image 172:



For the Image 172, our approach seems to capture most of the main defects. The result is not as successful as the previous two comparison images but still it gives meaningful results.

Discussion:

The evaluation of our approach on five different linen images revealed nuanced performance outcomes. Notably, the first two images, characterized by a simple line defect with a very small surface area, posed a challenge for our algorithm. The limitations were attributed to the inherent nature of the 2D moving average technique, which tends to smooth out finer details, making small defects less noticeable. The algorithm's struggle with these specific images underscores the need for complementary methods, especially when dealing with defects of minimal surface area.

Conversely, the algorithm demonstrated satisfactory performance on the remaining three linen images, showcasing its effectiveness in identifying defects in cases where the spatial characteristics were more pronounced. The inherent spatial dependencies in linen textures were effectively captured by the 2D moving average, leading to improved defect detection. The statistical control aspects further contributed to the robustness of the results, ensuring consistency and reliability in identifying deviations from expected patterns.

This dichotomy in performance highlights the importance of a versatile and adaptive approach. Recognizing the limitations of the 2D moving average for smaller defects, future iterations of the algorithm could benefit from the incorporation of additional control charts tailored for detecting finer anomalies. The combination of techniques, each optimized for specific defect characteristics, has the potential to enhance overall performance and provide a more comprehensive solution for quality control in linen manufacturing. As the objective of any defect detection system is to capture a wide range of anomalies, adapting the algorithm to accommodate various defect sizes and surface areas becomes imperative for its practical utility in diverse linen production scenarios.

In conclusion, while our approach exhibited noteworthy success in capturing defects in linen images with prominent spatial features, the findings underscore the necessity of refining the algorithm to address the challenges posed by smaller surface area defects. The discussion opens avenues for future work, emphasizing the potential benefits of combining multiple control charts and leveraging more advanced techniques to ensure a comprehensive and adaptable solution for linen quality control.

Conclusions and Future Work

The proposed method of the control chart combined with the moving average smoothing approach on linen patch detection has yielded promising results on the objective image. The adaptation of control procedures to the spatial characteristics of linen images provides a more accurate means of defect detection. However, challenges arise when dealing with thin or line-shaped defects, leading to limitations in the method's success. Despite these challenges, the overall performance on other image samples indicates the potential of the approach for robust defect detection in most scenarios.

Future Work and Recommendations for Improvement:

1. Enhanced Sensitivity for Thin Defects:
   - Future work should focus on refining the method's sensitivity to thin or line-shaped defects. This could involve exploring alternative normalization techniques or adjusting control chart parameters to better capture subtle variations in the image data.
2. Adaptive Control Chart Parameters:
   - Implementing adaptive control chart parameters could enhance the method's adaptability to diverse defect characteristics. Dynamic adjustment of parameters based on the nature of the fabric could improve the method's performance across a wider range of defect types and sizes.
3. Incorporation of Advanced Image Processing Techniques:
   - Integrating advanced image processing techniques, such as edge detection or texture analysis, can supplement the control chart approach. Combining these methods with the existing approach may provide a more comprehensive defect detection system capable of handling various defect shapes and sizes.
4. Machine Learning:
   - Integration of machine learning algorithms may further improve the accuracy of defect identification. It should involve expanding and diversifying the dataset used for training and validation. Including a broader range of defect types and characteristics will contribute to a more robust and versatile defect detection model.

REFERENCES

[1] Ersöz, T., Zahoor, H., & Ersöz, F. (2021). Fabric And Production Defect Detection In The Apparel Industry Using Data Mining Algorithms. *International Journal of 3D Printing Technology and Digital Industry*, 5(3), 742-757.

[2] Çelik, H. İ., Dülger, L. C., Öztaş, B., Kertmen, M., & Gültekin, E. (2022). A Novel Industrial Application of CNN Approach: Real-Time Fabric Inspection and Defect Classification on Circular Knitting Machine. *Tekstil ve Konfeksiyon*, Volume 32, No.4

APPENDIX

Appendix A: Link to Code - 2D Moving Average Implementation

[A] 423 Project Part 3_html.html

Appendix B: Link to responses of utilized LLM:

[B] https://chat.openai.com/share/a66c8bf6-f21b-4f96-bd3b-93a8ac9b03ad