IE 423 QUALITY ENGINEERING

PROJECT PART 3

QUALITY CONTROL ON IMAGES

CONTROL CHART BASED APPROACH ON LINEN DEFECTS ANALYSIS IN MANUFACTURING ENVIRONMENT

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Starting Notice: As Group 10, we were supposed to work with image id 0050, however, that name was not present at the image list, so we worked with image id 0048 to initiate certain statistical methods and the approach.

1. Introduction

Linen, a sustainable textile, is derived from the cellulosic fibers of the flax plant's stem. This nomenclature extends to both the fiber and the fabric. Notably, linen fibers exhibit a strength that is approximately two to three times greater than that of cotton fibers, coupled with a markedly higher rate of moisture evaporation, resulting in fabrics that are notably cool and highly absorbent. Its inherent porous quality renders linen an effective conductor of heat, making it a material of choice for summer clothing and bedding. [1]

In the realm of textile applications, linen is predominantly utilized in the fabrication of garments such as dresses, suits, and skirts, as well as in home fashion items including curtains, bed linens, and towels. The identification of defects in these end-products is of paramount importance to manufacturers within these sectors. Traditional human-centered detection methodologies are not only cost-intensive but also susceptible to a multitude of errors. One widely employed method in offline quality control involves halting production to extract product samples for testing. This interruption in production inherently escalates monitoring costs. The adoption of advanced image processing techniques for quality control could markedly enhance defect detection, affording manufacturers the opportunity to adjust their processes more efficiently and at a reduced cost.

Furthermore, it is imperative for entities such as laundries, textile manufacturers, and chemical vendors to meticulously monitor and control the production process of linen. Failure to do so may lead to undesirable outcomes during the washing process. [2]

2. Background Information

Key fabric defects of interest to manufacturers typically include warp or weft thread irregularities, oil stains, and holes. Warp or weft thread irregularities refer to texture inconsistencies in certain areas of the fabric, a common issue in linen inspections for this project. Oil stains, often resulting from lubricants used in textile machinery, represent another prevalent defect. Additionally, void areas in fabric, arising from friction during the movement of fabric rolls, are also considered defects[3].

In the realm of image processing, the application of grayscale filtering and binarization is a prevalent technique. Binarization involves setting a threshold for the grayscale image and categorizing pixels as either one or zero, corresponding to white and black, respectively. Threshold determination can be initially approached through basic histogram analysis, although more sophisticated methods such as clustering, interclass variance, and entropy are also documented. Subsequent to binarization, further modifications may be employed to enhance image clarity by consolidating larger white and black regions and minimizing inconsequential white areas[4].

Post-filtering and image modification, numerous studies concentrate on data mining techniques for defect detection and classification. For instance, semi-algebraic networks have been utilized for identifying defective and non-defective areas, while a modified version of K-means clustering has been employed in another study. An entirely algebraic approach for defect detection, eschewing data mining, is explored in another research, utilizing white and black intensity variations in binarized image sections and analyzing the disparity in white and black pixel counts in adjacent rows. For defect classification, methodologies such as neural networks and fuzzy c-means algorithms have been applied in various studies.

3. Approach

The initial approach that we developed is based on, employing grid-based segmentation combined with statistical analysis. The technique segments an image into a 16x16 grid, calculates the mean and standard deviation of pixel intensities for each segment, and establishes baseline statistics for the entire grid. Anomalies are identified in segments where mean intensities deviate by more than ±2 standard deviations from the baseline. This method not only detects but also visually highlights anomalies, aiding in the rapid identification of irregular patterns or defects.

The core of our methodology involves a four-step process:

Segmentation: The image is divided into a grid of 256 (16x16) equal segments. This granularity allows for detailed analysis without excessive computational demands.
Feature Calculation: For each segment, we compute the mean and standard deviation of pixel intensities. These metrics are chosen for their sensitivity to variations in image texture and brightness.
Baseline Statistics: We then calculate the overall mean and standard deviation across all segments. This establishes a baseline, serving as a reference point for identifying anomalies.
Anomaly Detection: Anomalies are flagged in segments where the mean intensity falls outside ±2 standard deviations from the baseline mean. This threshold is selected for its balance between sensitivity and specificity.

Key to our approach is the effective visualization of results:

The segmented grid is overlaid on the original image, providing a clear reference for each segment. Histograms of mean and standard deviation values across all segments are displayed, offering an overview of the distribution. Segments identified as anomalies are highlighted, directing attention to potential areas of concern.

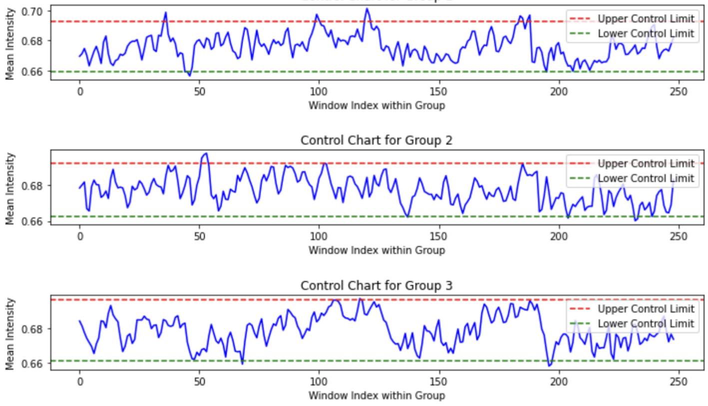
Finally, the system outputs the control limits and precise locations of detected anomalies, facilitating further analysis or corrective measures.

The initial approach provides visually satisfactory defects in the image capture of the linens. This grid method can provide a good basis of batch grouping strategy for the defect detection. But this method mainly assumes that each grid is independent of each other. In pictures the pixels are mostly dependent on each other due to the context and the integrity of the image. However, for further improvement purposes, we developed a further method based on the intersection of the window capture. The method can be followed as follows.

The function processes an image for anomaly detection using a sliding window technique and statistical analysis, and then displays the results. Here's a breakdown of its steps:

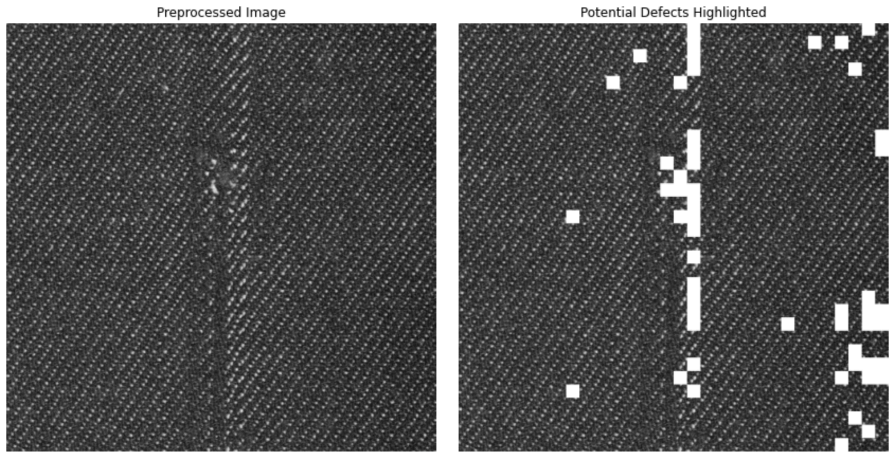
Load Image: The image is loaded from the specified path (image_path). It's converted to grayscale for analysis.
Sliding Window Analysis: A window of specified size (window_size) slides over the image in steps (step_size). The mean pixel intensity is calculated for each window position. The window's top-left corner positions are tracked.
Grouping and Statistical Analysis: The sliding windows are grouped into 32 groups (num_groups). The mean and standard deviation are calculated for each group. Control limits are set at ±2 standard deviations from the mean for each group.
Anomaly Detection: Windows with mean intensities outside their group's control limits are marked as anomalies. Pixels in these anomalous windows are set to white in the grayscale image array.
Visualization: Two images are displayed side-by-side: The original grayscale image.
The modified grayscale image with anomalies highlighted in white. The visualization helps to compare the original and processed images, highlighting the detected anomalies.
Usage: To use the function, you pass the path to an image (e.g., '0048.jpg'). The function processes this image and displays the results.

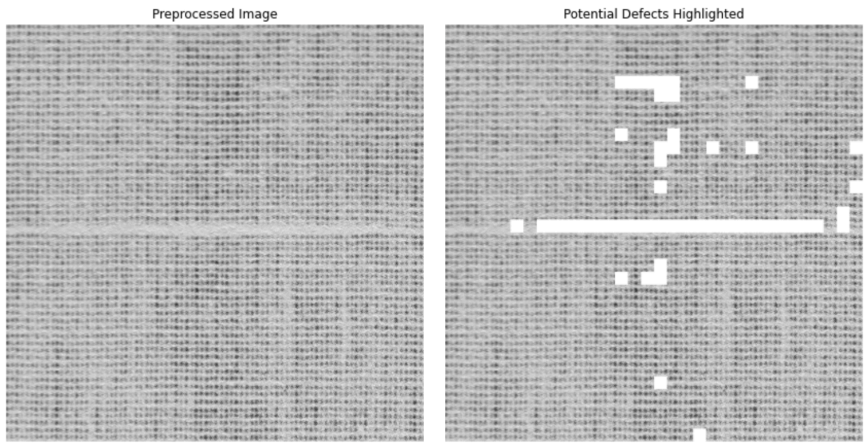
This function is particularly useful for identifying areas in images that significantly deviate from the average or expected pixel intensity patterns. By using statistical process control principles, it can highlight unusual spots, which could be indicative of anomalies or defects in the image. The visualization aspect makes it easier to see where these potential anomalies are located relative to the original image.



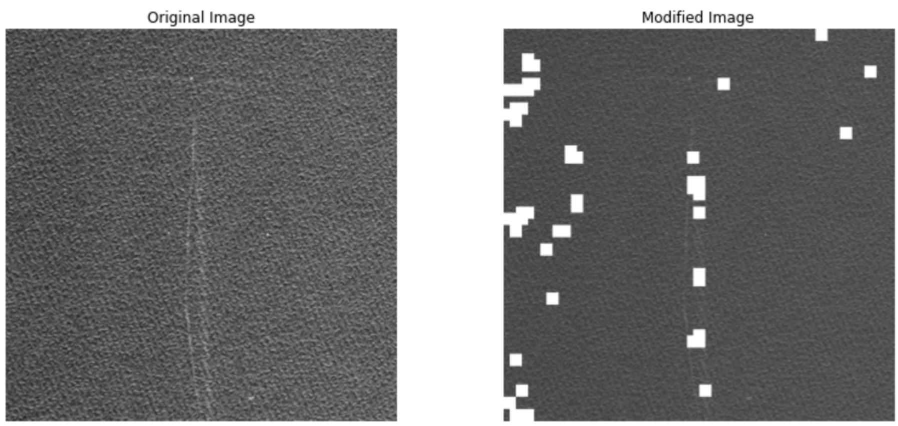
4. Results

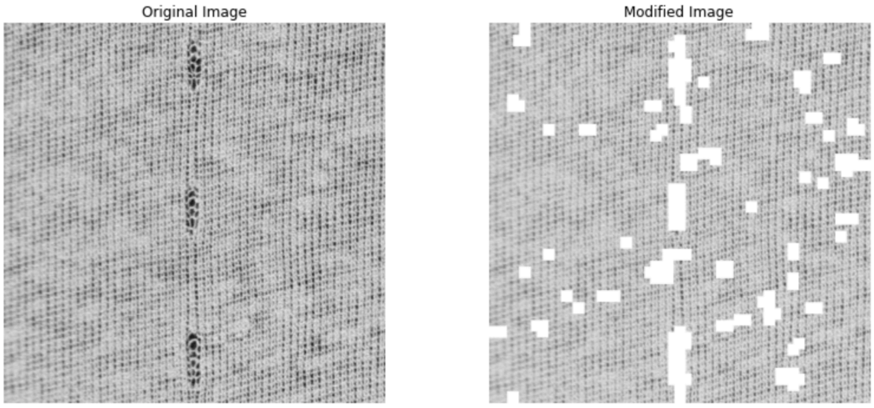
Grid Based Approach:





Sliding Window Technique:





Sliding Window Method:

Principles:

Window Sliding: A fixed-size window slides across the image, typically with a defined step size, analyzing one portion of the image at a time.

Local Analysis: At each position, statistical metrics (e.g., mean, standard deviation) of pixel intensities within the window are calculated.

Overlapping Analysis: Adjacent windows often overlap, allowing for more continuous and comprehensive coverage of the image.

Anomaly Detection: Anomalies are detected based on deviations in these metrics from established norms or thresholds.

Error Detection: Effective in identifying local anomalies, especially where fine-grained analysis is required. Overlapping windows provide more sensitivity to subtle changes in texture or intensity.

Grid-Based Method:

Principles:

Fixed Segmentation: The image is divided into a grid of non-overlapping segments or blocks, each analyzed independently.

Uniform Analysis: Each segment is analyzed using statistical metrics similar to the sliding window method.

Non-Overlapping: Segments are distinct and do not overlap, providing a more compartmentalized analysis.

Anomaly Detection: Segments with statistical metrics falling outside predefined control limits are flagged as anomalies.

Error Detection: Suitable for detecting anomalies that are expected to occupy larger, more distinct areas of an image. Less sensitive to small or subtle anomalies due to the non-overlapping and uniform nature of the segments.

Comparison:

Coverage and Sensitivity: The sliding window method offers more thorough coverage and sensitivity to small changes due to overlapping windows. The grid-based method might miss subtle anomalies due to its non-overlapping nature.
Computational Efficiency: Grid-based methods can be more computationally efficient, as they involve fewer calculations (no overlapping areas).
Simplicity and Interpretability: Grid-based analysis is often simpler and more interpretable, with clear boundaries for each analyzed segment.
Error Detection Appearance: Both methods might highlight similar anomalies in an image, particularly if the anomalies are large or pronounced. However, the sliding window method might detect smaller or more subtle anomalies that the grid-based method could overlook due to its finer and overlapping analysis.

In conclusion, the choice between these two methods depends on the specific requirements of the anomaly detection task, including the nature of expected anomalies, the level of detail required, and computational constraints. The sliding window approach is preferable for detailed and sensitive analysis, while the grid-based method is more suitable for broader, less granular anomaly detection.

5. Conclusion and Future Work

The approach utilized grid-based segmentation then further sliding window technique and statistical process control (SPC) techniques to identify anomalies in images. Key aspects of the approach included:

Grid-Based Segmentation: Images were divided into smaller segments, allowing localized analysis of pixel intensity variations.

Sliding Window Technique: This technique enhanced the ability to detect localized anomalies by analyzing overlapping regions of the image.
Statistical Analysis: For each segment, descriptive statistics (mean and standard deviation) were calculated, providing a basis for anomaly detection.
Control Chart Implementation: Using SPC principles, control limits were set, and segments with mean intensities falling outside these limits were flagged as potential anomalies.
Visualization: The process included visualizing the original and processed images, with anomalies highlighted, facilitating an intuitive understanding of the results.

Overall, the method effectively identified segments with unusual pixel intensity distributions, suggesting potential anomalies. The use of statistical process control in image analysis is innovative, combining traditional quality control techniques with image processing.

To enhance this approach and address its limitations, certain extensions can be considered.

Dynamic Control Limits: Implement adaptive control limits that adjust based on different regions or types of images, taking into account the inherent variability in different image datasets.
Automated Segmentation: Explore automated segmentation techniques, like clustering or edge detection, to define segments dynamically based on the image's content rather than a fixed grid.
Advanced Texture Analysis: Incorporate more sophisticated texture analysis methods to capture more complex patterns and variations in images due to the shadow effects or coloring lights.

6. References

[1] https://www.norvilsa.com/en/linen-fabric-all-you-need-to-know-about-this-fabric
[2] https://www.houseofu.com/en/blog/the-properties-of-linen-all-about-this-fabric/
[3] Jmali Mohamed, Zitouni Baghdadi And Sakli Faouzi " Classification of Fabrics Defects Using Image Analysis and Fuzzy C‐Means Method", International Conference of Applied Research On Textile, Citrat‐6, Hammamet, Tunisia, November 13 – 15, 2014.
[4] Blaga Mirela (2009): "Computer Vision Systems for Textiles Quality Control", The 6th International Conference Management of Technological Changes, Greece, September 2009.

7. Appendices

[1] Jupyter Notebook Code File