IE 423 Quality Engineering
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Project Part 3

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1. Introduction

Linen, a textile crafted from the fibers of the flax plant, is renowned for its unique properties, particularly its exceptional coolness and freshness in hot weather. Ensuring the quality of linen products throughout the manufacturing process is of paramount importance. The motivations behind using images and identifying defects in linen manufacturing are multifaceted.

Firstly, quality assurance is a primary driver. Linen manufacturers aspire to produce goods that consistently meet or exceed customer expectations. By actively monitoring the linen production process, manufacturers can identify and rectify any defects or irregularities promptly. This proactive approach helps maintain the desired level of quality, preventing subpar products from reaching customers.

Secondly, cost reduction is a significant consideration. Early detection of defects in the manufacturing process is instrumental in minimizing waste and optimizing production efficiency. By identifying and addressing defects at an early stage, manufacturers can reduce the need for costly rework or the disposal of flawed products, ultimately resulting in cost savings.

Furthermore, customer satisfaction is a critical aspect of the linen industry. Delivering defect-free linen products ensures that customers receive items that meet their quality expectations. Satisfied customers are more likely to become repeat buyers and advocates for the brand, contributing to long-term success and reputation in the market.

Lastly, efficiency improvement is another driving factor. Automation of visual inspection using images streamlines the quality control process. This automation is particularly beneficial when dealing with large quantities of products that require inspection. Automated defect detection can significantly reduce labor costs and increase overall production efficiency.

In summary, the use of images and defect identification techniques in linen manufacturing serves to uphold quality standards, reduce production costs, enhance customer satisfaction, and improve production efficiency. These motivations underscore the significance of image-based quality control in the linen industry.

2. Background Information

The research paper "Auto: A Computer Program For The Determination Of The Two-Dimensional Autocorrelation Function Of Digital Images" by S. Pfleiderer, D. G. A. Ball, and R. C. Bailey, while not directly focused on linen, offers valuable insights into advanced image processing techniques that can be applied to the analysis and quality control of linen fabrics.

2.1 Analysis of Fabric Structure and Anisotropy

The AUTO program's capability in analyzing fabric structure and anisotropy using the two-dimensional autocorrelation function (ACF) is highly applicable to linen. Linen, with its unique weave patterns and structural features, can be quantitatively analyzed to assess alignment, distribution, and uniformity, which are crucial for determining quality and durability.

2.2 Quality Control and Process Monitoring in Linen Production

The ability of the AUTO program to statistically characterize fabric images is particularly beneficial for monitoring and controlling the quality of linen during production. This approach can help in detecting inconsistencies in weaving, fiber alignment, and density, thereby ensuring the consistent quality of linen products.

2.3 Material Characterization for Predicting Linen Performance

Understanding linen's microstructure is essential for predicting its performance characteristics. Using the ACF method, manufacturers can gain insights into the fabric's mechanical properties such as tensile strength and wear resistance, which are influenced by the orientation and distribution of the fibers.

2.4 Innovation in Linen Fabric Design

The principles outlined in the paper can also drive innovation in linen fabric design. The quantitative analysis of different weaving techniques and fiber treatments allows for the development of novel linen textures and patterns, paving the way for new and improved products in the linen market.

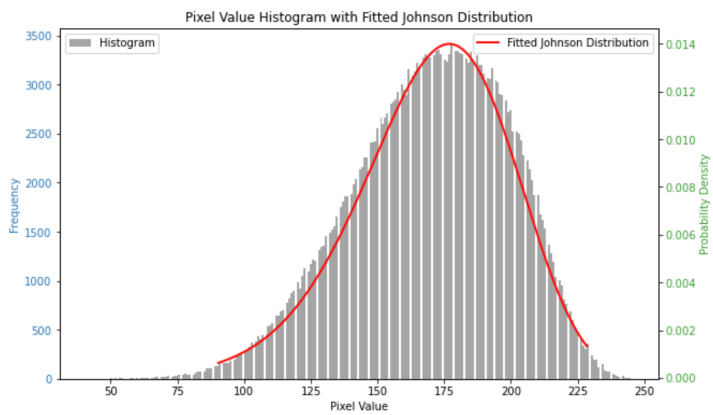
In conclusion, the methodologies presented in the paper, though not specific to linen, hold significant potential for enhancing the analysis, quality control, and development of linen fabrics. The application of these advanced image processing techniques could lead to notable advancements in the linen industry, improving both product quality and innovation.

3. Approach

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

Task 1: *Histogram Analysis and Probability Distribution Fitting*

The first step in our approach involves generating a histogram of the pixel values from the image of the linen fabric. This histogram serves as a visual representation of the distribution of pixel intensities across the image, providing a baseline for further analysis. To appropriately model this distribution, we employ the Kolmogorov-Smirnov (KS) test to various probability distributions. Our initial focus is on the normal distribution, which shows promising results. However, to confirm the suitability of this distribution, we implement a Quantile-Quantile (Q-Q) plot. This plot is overlaid on the histogram to assess how well the normal distribution aligns with the observed data. While the results from this step provide valuable insights, they do not fully meet our criteria for a satisfactory fit. Consequently, we explore alternative distributions, specifically the skewed normal and Johnson distributions. The Johnson distribution, in particular, yields impressive results, with the Q-Q plot demonstrating a close fit to the observed data.



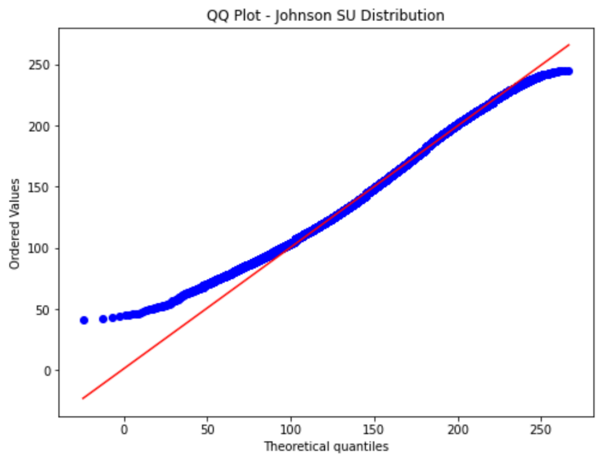


Chart 1: Histogram with Fitted Johson's SU-Distribution

Chart 2: Q-Q Plot for Johnson's SU-Distribution

Task 2: *Parameter Estimation of the Chosen Distribution*

After identifying the Johnson distribution as the most suitable model for our analysis, we focus on estimating its parameters using the image data. The accuracy of these parameters is critical as they define the unique characteristics of the distribution, specifically tailored to match the pixel values of the linen image. The Johnson distribution is characterized by four key parameters: δ (shape parameter), ξ (location parameter), λ (scale parameter), and γ (shape or gamma parameter).

In our analysis, these parameters are meticulously estimated to reflect the specific distribution of pixel intensities within the linen fabric image. The estimated values are as follows:

- λ (scale parameter) is estimated at 10.134863891539586. This parameter influences the skewness of the distribution, allowing the model to account for any asymmetry in the distribution of pixel values.

- δ (shape parameter) is determined to be 5.867287122342922. This parameter shifts the distribution along the intensity scale, ensuring that it aligns accurately with the central tendency of the pixel values in the image.

- γ (shape parameter) is calculated to be 331.12483051492563. This parameter affects the spread of the distribution, enabling it to encapsulate the range of pixel intensities observed in the linen fabric.

- ξ (location parameter) is found to be 58.32355605328308. This parameter further refines the shape of the distribution, ensuring that it accurately represents the intricacies of the pixel intensity pattern.

These estimated parameters are critical for ensuring that the Johnson distribution closely matches the characteristics of the pixel intensity distribution in the image. By accurately estimating these parameters, we can effectively model the distribution of pixel values, which is essential for the subsequent steps in our analysis, particularly in identifying and modifying outlier pixels.

Task 3: *Identification and Modification of Outlier Pixels*

Upon establishing the Johnson distribution and its specific parameters, we embark on the task of identifying pixels that deviate significantly from the established norm. This is achieved by defining the probability limits of the distribution - specifically, we look for pixels that fall outside the 0.001 probability bounds. These bounds are set to exclude the most extreme 0.1% of observations, both on the lower and upper ends of the distribution spectrum.

In this process, pixels that reside beyond these predetermined thresholds are flagged as outliers. These outliers are presumed to be anomalies in the context of the fabric's typical pattern. Once identified, we modify these outlier pixels by setting their values to zero, thus turning them black. This alteration serves to visually highlight areas of the fabric that significantly deviate from the expected distribution of pixel values.

However, upon reviewing the results of this approach, we encounter a significant limitation. The method, as it stands, evaluates each pixel in isolation, considering only its intensity value without regard to its surrounding context. Consequently, this approach proves inadequate in identifying true irregularities in the fabric structure. Instead, it merely accentuates the most extreme pixel values in terms of brightness or darkness, without providing meaningful insight into pattern anomalies or inconsistencies.

This realization prompts a need for a more nuanced approach, one that accounts for the spatial relationships and patterns within the fabric. By considering the collective behavior of pixel groups, rather than individual pixels in isolation, we can more accurately identify areas of the fabric that deviate from the expected norm in a way that is significant and indicative of actual fabric irregularities. Therefore, while the initial results of identifying and modifying outlier pixels provide a starting point, they underscore the necessity for a more contextually aware method that can better capture and represent the complexities of fabric patterns and irregularities.

Task 4:*Analyzing Pixel Value Distributions in 51x51 Windows*

The final task extends our approach to smaller, localized sections of the image, known as patches. This is particularly important when local structures within the fabric are crucial, as is often the case with materials like linen where weave patterns can vary significantly over small areas. We assume a patch (window) size of 51x51 pixels and apply the same methodology used in the first three tasks to each of these patches.

This localized approach allows us to analyze the fabric more thoroughly, identifying anomalies at a more granular level. While this approach discovers more local inconsistencies and yields better results than Task 3, it is important to note its limitations. By focusing on smaller patches, this method may overlook autocorrelation and dependencies between neighboring pixels, which could be relevant in certain contexts.

As in the previous step, we mark the outlier pixels within each patch. These marked pixels are then set to zero, turning them black. The result is a detailed image that highlights even the smallest areas of inconsistency across the fabric. By presenting this newly processed image alongside the original, we provide a comprehensive view of how local variations and irregularities distribute across the entire piece of linen.

This structured, multi-step approach allows for a thorough and detailed analysis of the linen fabric, ensuring that both global and local inconsistencies are accurately identified and visually represented. Despite the effectiveness of our localized approach in identifying anomalies within smaller patches, it is important to acknowledge a notable drawback associated with this method. By exclusively focusing on the distribution of pixel values within each patch, we may inadvertently overlook the spatial relationships and dependencies between neighboring pixels.

This drawback becomes particularly relevant in scenarios where autocorrelation plays a significant role, such as in textured surfaces or patterns with spatial coherence. In such cases, anomalies may exhibit a more complex spatial structure that goes beyond the scope of our patch-based analysis.

Consequently, our method might not fully capture certain irregularities that emerge from the interactions between adjacent pixels.

3.2 A Simple Defect Detection Approach from a Control Chart Perspective

Despite estimating that pixel values follow a Johnson SU distribution, a more flexible version of the normal distribution, we made a pragmatic choice during the construction of control charts. While the Johnson SU distribution offers increased flexibility in modeling various shapes of data distributions, our approach was guided by the assumption that, for the purpose of building control charts, adhering to the normality assumption would be adequate. Therefore, in the context of control chart analysis, we utilized parameters corresponding to the normal distribution, namely the mean and sigma, under the assumption that the Johnson SU distribution, in this instance, doesn't significantly violate the normality assumption. This decision allowed for a straightforward application of control chart principles while maintaining computational efficiency.

Task 5: *Row-wise Control Chart Analysis:*

For each row of the image, we construct control charts to monitor the mean and variance of pixel values. Pixels that deviate from the expected behavior (out of control) are identified and set to zero. The new image, showcasing adjustments made based on row-wise control chart analysis, is compared with the original image. Observations and findings provide insights into the consistency of pixel values across the image's horizontal axis.

Row-wise control chart analysis allows us to identify and address out-of-control pixels along the horizontal axis of the image. However, for our specific case, it's observed that the defected area exhibits a horizontal pattern. While this approach is informative, the subsequent analysis reveals that the column-wise control chart analysis is more effective in detecting anomalies within the linen fabric since our fabric is defected horizontally.

Task 6: *Column-wise Control Chart Analysis*

Control charts are constructed for each column of the image, monitoring mean and variance. Out-of-control pixels are detected and modified. The new image resulting from column-wise adjustments is compared with the original image, providing insights into potential defects related to the vertical distribution of pixel values.

In our specific case, the column-wise control chart analysis proves to be more effective for defect detection. The defected area in the linen fabric exhibits a horizontal pattern, making the vertical column-wise analysis better suited for identifying and addressing anomalies. It's essential to recognize the specific characteristics of the linen fabric under consideration, as the effectiveness of row-wise or column-wise approaches may vary based on the nature of the defects.

In summary, while the column-wise approach is more appropriate for our specific case where defects manifest horizontally, it's crucial to consider the unique features of the fabric. Nevertheless, it's important to note that a comprehensive solution should still account for autocorrelation and other spatial relationships within the fabric, and further analyses may be necessary for a thorough defect detection process.

3.3 Proposed Approach for Defect Detection in Images Using Two Dimensional Statistical Process Control

Our approach for defect detection in images takes inspiration from statistical process control techniques, adapted to address the unique challenges posed by spatial data in 2D images. This method is particularly effective for images with textures, where pixel values are interrelated, making traditional control charts that assume independence less effective.

Step 1: *Cross-Correlation for Texture Analysis*

The core of our approach revolves around the use of two-dimensional cross-correlation, a method that allows us to understand the relationships between pixel values across an image. We begin by normalizing the pixel values to a uniform scale, typically between 0 and 1, to ensure consistency in the data. We then create a small averaging filter, often a 3x3 matrix, which serves as a kernel for the cross-correlation process. This kernel is systematically applied across the image, analyzing local groups of pixels to identify patterns and textures. The cross-correlation is computed in such a way that the resulting values have the same dimensions as the original image, with special consideration given to how the edges of the image are treated.

Step 2: *Establishing Control Charts for Anomaly Detection*

The next step involves the application of control chart principles to the cross-correlation values obtained from the image. We calculate the mean and standard deviation of these values to establish a statistical baseline of what is considered normal variation in the image's texture. From these statistics, we set upper and lower control limits, determining thresholds beyond which pixel values are deemed anomalous. These limits are pivotal in differentiating between normal texture variations and potential defects.

Step 3: Identifying and Marking Defective Regions

With the control limits in place, we proceed to scrutinize the cross-correlation values across the image. Regions where the values exceed the established thresholds are flagged as potential defects. These areas are marked, often by altering the pixel values to make them visibly distinct from the rest of the image. This step is crucial in visually highlighting the areas of the fabric that may have irregularities or inconsistencies in texture.

Step 4: Overcoming Autocorrelation Challenges

A significant advantage of this method is its ability to address the issue of autocorrelation, a common challenge in image analysis, especially when dealing with textured surfaces. By focusing on the relational aspects of pixel values rather than treating them as independent entities, our approach provides a more nuanced and accurate detection of defects in fabrics and other textured materials.

This innovative approach presents a comprehensive and effective solution for defect detection in images, merging the rigors of statistical process control with the depth of two-dimensional image analysis. It enables a thorough examination of pixel relationships using cross-correlation and control charts, adeptly identifying and accentuating areas that may indicate issues in materials with complex textures. This technique is particularly valuable for examining materials where conventional defect detection methods might not provide a full picture.

Importantly, the efficacy of this approach has been demonstrated not only on the initially assigned linen sample but also on an additional five linen samples. In each case, our method successfully detected abnormalities, highlighting its robustness and reliability across various textures and patterns found in linen fabrics. These results underscore the potential of our two-dimensional statistical process control approach in a broad range of textile quality assurance applications, offering a significant advantage in ensuring the consistency and quality of linen products.

4. Results and Comparison

In our analysis of linen quality control, we've used various approaches to detect defects in the manufacturing process, each presenting unique strengths and limitations.

Baseline Defect Detection Approach (Task 1-4):

Our initial tasks involved histogram analysis and probability distribution fitting, revealing the suitability of the Johnson distribution for modeling pixel intensity. Subsequently, parameters for the Johnson distribution were accurately estimated, and outlier pixels were identified and modified. However, this method lacked contextual awareness, evaluating pixels in isolation, leading to potential oversights in detecting true irregularities in fabric structure. The analysis of 51x51 windows provided more localized insights but had limitations in handling autocorrelation and dependencies between neighboring pixels.

Control Chart Approaches (Task 5-6):

Row-wise control chart analysis effectively identified and modified out-of-control pixels along the horizontal axis, while the column-wise control chart proved more adept at detecting anomalies aligned with the observed horizontal pattern in our specific case. However, both approaches, while efficient for specific patterns, might fall short in capturing nuanced spatial relationships within the fabric.

Proposed Two-Dimensional Statistical Process Control Approach (Task 7):

Our innovative approach, combining cross-correlation for texture analysis and control charts, demonstrated superior performance in defect detection. By addressing autocorrelation challenges and considering spatial dependencies, this approach showcased versatility and robustness across various linen samples.

Comparison and Insights:

While the baseline and control chart approaches provided valuable insights, the proposed two-dimensional statistical process control approach stood out for its ability to comprehensively address spatial dependencies and autocorrelation challenges.

5. Conclusions and Future Work: Reflections and Prospects

Our proposed two-dimensional statistical process control approach for defect detection in images, particularly those with textured surfaces like linen fabrics, has demonstrated its effectiveness. This approach, which combines cross-correlation analysis with control chart techniques, has successfully identified areas indicative of defects in materials with complex textures.

The approach was effective not only with the initially assigned linen sample but also with five additional linen samples, highlighting its robustness and reliability across various textures and patterns. This success underscores the potential of our approach in a broad range of textile quality assurance applications.

However, the study also revealed the need to better address autocorrelation and dependencies between neighboring pixels. Future enhancements should focus on incorporating more sophisticated image processing techniques or exploring machine learning algorithms to improve pattern recognition and anomaly detection in complex fabric structures. Such advancements could further refine the methodology, ensuring higher accuracy and reliability in defect detection across a wider range of fabric types.

Resources

George, Florence and Ramachandran, K. M. (2011) "Estimation of Parameters of Johnson's System of Distributions," Journal of Modern Applied Statistical Methods: Vol. 10 : Iss. 2 , Article 9.

S. Pfleiderer, D.G.A. Ball, R.C. Bailey, AUTO: A computer program for the determination of the two-dimensional autocorrelation function of digital images, Computers & Geosciences, Volume 19, Issue 6, 1993, Pages 825-829,

Rimac-Drlje, Snježana & Žagar, Drago & Rupcic, Slavko. (2010). Adaptive image processing technique for quality control in ceramic tile production. 52. 205-215.